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Survey on WiFi-based indoor positioning techniques

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Abstract: With the rapid development of wireless communication technology, various indoor location-based services (ILBSs) have gradually penetrated into daily life. Although many other methods have been proposed to be applied to ILBS in the past decade, WiFi-based positioning techniques with a wide range of infrastructure have attracted attention in the field of wireless transmission. In this survey, the authors divide WiFi-based indoor positioning techniques into the active positioning technique and the passive positioning technique based on whether the target carries certain devices. After reviewing a large number of excellent papers in the related field, the authors make a detailed summary of these two types of positioning techniques. In addition, they also analyse the challenges and future development trends in the current technological environment.

1 Introduction

With the continuous development of wireless technology, people pay more and more attention to location-based service (LBS). In recent years, LBS has been widely used in different environments to provide users with location identification, navigation and other services to meet the positioning demand of different groups of people. In the outdoor, most of the positioning demands are also met in accuracy due to the maturity of the global positioning system (GPS) technology. In addition, the global navigation satellite system (GNSS) and assisted global positioning system have further improved the accuracy and range of outdoor positioning.

As the focus of research moves from outdoor to indoor, the performance of these positioning systems is often unsatisfactory and cannot be applied to practice due to weak GPS signals and the complexity of indoor environments with multiple obstacles. In the past decade, great progress has been made in using other methods to study indoor LBSs (ILBSs) [1, 2]. There are many technologies for indoor positioning, such as visual technology, infrared technology, WiFi technology, ultra-wideband technology, bluetooth technology, inertial navigation technology and magnetic technology. Diverse methods provide new insights for prospective researchers [3, 4]. In recent years, various methods have been compared, and their advantages and disadvantages have been analysed.

Nowadays, the popularity of smartphones and a series of WiFi terminals has further promoted the rapid development of ILBS. Ubiquitous WiFi makes relevant indoor positioning techniques widely used in public safety, industry, medical treatment and other fields. From the current application scenes of ILBSs, WiFi technology has the following three advantages: (i) *Widely distributed hot spots*: WiFi hotspots can be distributed in various large or small buildings such as homes, hotels and shopping malls, which makes WiFi positioning suitable for many indoor environments. (ii) *Low access conditions*: due to the widespread distribution of existing WiFi infrastructure, most of the WiFi-based positioning systems do not need to rebuild or expand the network, which reduces application costs. (iii) *High flexibility*: WiFi signals are not severely affected by not line of sight (NLOS) in the complex indoor environment.

This survey aims to provide readers with a comprehensive overview of WiFi-based indoor positioning techniques. This paper describes and compares relevant techniques and systems to provide guidance for workers and researchers in related fields and help them understand the latest developments in this field in recent years. The main contributions of this survey are as follows:

(i) To the best of our knowledge, this is the first sufficient survey of WiFi-based indoor positioning techniques from the perspective of active and passive positioning. Unlike most other surveys that focus on specific positioning algorithms, this survey is based on whether the target carries certain devices.
(ii) We conduct a comprehensive comparison and analysis of the two techniques of active positioning and passive positioning. We list the requirements and challenges of these two technologies in practice. In addition, we introduce WiFi-based positioning systems combined with other positioning technologies, and analyse the applicability and advantages and disadvantages of these systems.
(iii) In response to the challenges, we discuss open research issues about WiFi positioning.

The rest of this survey is organised as follows. Section 2 introduces different ILBSs for active and passive positioning techniques. Section 3 introduces related research based on active indoor positioning technique. In Section 4, we introduce related research based on passive indoor positioning technique. Section 5 discusses the issues that need to be addressed and the future direction of WiFi-based indoor positioning techniques. Section 6 summarises this paper.

2 Application scenarios

2.1 Performance requirements

The development of wireless local area network makes research on ILBSs more and more popular. Simultaneously, researchers have achieved amazing development in recent years. According to whether the user carries certain devices, we divide WiFi-based indoor positioning techniques into the active positioning technique and the passive positioning technique. Active positioning [5, 6] means that the user needs to carry a mobile device to actively search and collect signals of nearby APs, which is the most commonly used form in daily life. The valid information from the signals of APs can be obtained, and then the information is transmitted to the server for processing. The system determines the

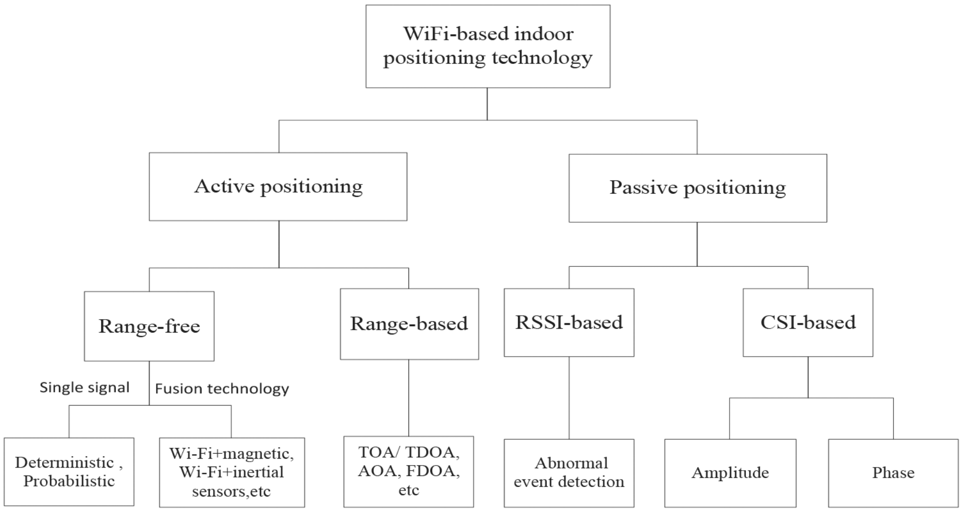


Fig. 1 *Classification of WiFi-based indoor positioning*

user's location through some positioning algorithms. Passive positioning [7, 8] means that the user does not need to carry any equipment, but the signal transmitter and signal receiver need to be deployed. When the user enters the positioning area, he will affect the propagation of the signal. The signal receiver receives different signals when the user is in different positions. The system can estimate the user's position based on the signal changes. Compared with the passive positioning technique, the active positioning technique has higher positioning accuracy, but it is inconvenient for the user to carry the mobile device. Fig. 1 provides a detailed classification of WiFi-based indoor positioning systems from the perspective of active and passive positioning. The performance of various indoor positioning techniques is applicable to different indoor application scenarios, hence it is necessary to use a suitable indoor positioning technique in different ILBSs. This section introduces the requirements of indoor positioning techniques in different scenarios from aspects of accuracy, real-time, scalability, reliability and cost.

2.1.1 Accuracy: The primary purpose of ILBSs is to obtain the user's location, so the accuracy of positioning is one of the important indicators to measure the performance of different indoor positioning techniques. Of course, the requirements for positioning accuracy are different in different ILBSs. In many cases, other indicators such as cost, real-time and reliability need to be taken into account. For example, achieving ILBSs similar to location-based store recommendation services do not require high-precision location information. Excessive precision will only increase its cost and reduce its real-time performance, which in turn leads to a decrease in the overall system evaluation. Unlike the store recommendation services, indoor navigation similar to the route to the store requires more accurate location information so that other indicators can only be considered on the basis of meeting accuracy. Most of the current research focuses on how to improve the accuracy of indoor positioning. Tables 1 and 2 show the special requirements and accuracy of some active positioning systems. At the same time, the accuracy of other algorithms is added to these tables for comparison.

2.1.2 Real-time: Real-time is as important as accuracy in some specific indoor applications. For example, when the criminals hold the hostages, police need to know in real time the location of hostages in order to have more opportunities for rescue. When a disaster occurs indoors, panicked trapped people may move at any time, and it is necessary to locate the trapped person in real time during an emergency rescue by the rescue team. Most indoor positioning algorithms use methods that modify algorithm complexity, signal acquisition, AP deployment and hardware to improve the real-time performance of the indoor positioning technology.

2.1.3 Scalability: The scalability of indoor positioning technology is the ability of a system to adapt to changes in the environment after taking into account the required performance, cost, maintainability and other factors. When the system is expanded, the higher the system's scalability, the lower the additional cost required by the system and the lower the impact on other performance. Especially for commercial purposes, due to the increase of indoor users and the channel occupied by other wireless devices, the system processing capacity is overloaded. This factor degrades system performance, thus we have to improve the system. In addition, when expanded space is beyond the scope of the system, the system needs to make changes to software and additional equipments. High scalability ensures the system has a long life cycle. The linear increase in processing capacity and coverage of the entire system can be achieved by making some changes to the system or even adding only hardware devices.

2.1.4 Reliability: The reliability of positioning system includes three elements: specified time, operating environment and accuracy. Therefore, reliability can be described as the probability that the feedback results by indoor positioning techniques have no obvious error in a given time and environment. In some special indoor scenarios, such as mine and firefighting, reliability is one of the primary conditions for evaluating positioning techniques. Especially in the face of some unexpected situations, if the reliability cannot be guaranteed, ILBSs may report incorrect positioning results in the event of an emergency, which may make the situation even more out of control.

2.1.5 Cost: The cost will directly affect the application and popularity of ILBSs, hence its cost needs to be comprehensively considered in the design process of indoor positioning technology. Performance requirements, operating environment and hardware equipment affect its cost. Simultaneously, system maintenance and expansion costs are also major sources of the cost after the system design is completed. In recent years, due to the popularity of smart terminal devices and the development of wireless local area networks, the cost of ILBSs has been dropped significantly in many indoor scenarios.

2.2 Challenges

In practice, the following challenges must be overcome to achieve desired performances of ILBSs.

2.2.1 Multipath effect: As we all know, indoor space is very small and the complexity of the environment is much higher than the vast outdoor. It can be known from Fig. 2*a* that in addition to the direct signal, there may be many reflection signals when the WiFi signal is transmitted. These WiFi signals that arrive at the receiver through different paths cause a multi-path effect. Signal distortion caused by multi-path effects has a significant impact on improving the accuracy of indoor positioning technology.

2.2.2 Obstacle: At present, most WiFi signal propagation loss models are established when WiFi signals are transmitted from the transmitter to the receiver along the line of sight (LOS). In reality, WiFi signals encounter obstacles such as walls, doors and windows during communication, thus it is impossible to accurately estimate the signal loss, as shown in Fig. 2*b*. Although some researchers have analysed the signal loss values of different obstacles, the internal structure and thickness of the obstacle all affect the signal loss value. Especially, if WiFi signals are blocked by obstacles, the indoor positioning system based on deterministic algorithms will have significantly lower performance.

2.2.3 Device heterogeneity: There exists an obvious device heterogeneity when the user's smart device is different from the reference device. Fig. 2*c* shows the received signal strength (RSS) values from different APs collected by different mobile devices. It can be seen that device heterogeneity exists. The main factors affecting the heterogeneity of mobile devices include WiFi chips, WiFi antennas, hardware drivers, packaging materials and operating systems. Due to these factors, there are differences between the reference device and user's smart device which detects signal strength at the reference device position. WiFi-based indoor positioning technology is to estimate the location by converting RSS into different physical parameters, thus RSS differences caused by the heterogeneity of devices will affect positioning accuracy.

3 Active positioning

As one of the research directions of the WiFi-based indoor location technology, the related research of indoor active positioning has been quite mature and there are many achievements in related fields. Meanwhile, the popularisation rate of smartphones in the population has been quite high with the development of the smartphone industry. In addition, almost all smartphones on the market include the WiFi module, thus smartphones can be independently applied to various ILBSs. The low cost, high penetration rate and complete function make the smartphone have better applicability for each WiFi-based indoor positioning system. In this section, we review a large number of techniques and systems related to active indoor positioning. Most of these techniques or systems use the smartphone or the mobile device that can be replaced with a smart phone to experiment, while other systems do not require the positioning target to carry a specific WiFi receiving device. Moreover, we summarise these systems that

Table 1 Comparison of range-free-based positioning methods

Basic technique	Reference	Positioning accuracy of other algorithms	Positioning accuracy	Specific requirements
deterministic	[9]	2.12 m	1.56 m	pre-existing APs and n candidate APs
	[10]	—	about 1 m	—
	[11]	RSS-WKNN: 4.805 m SSD-WKNN: 4.666 m	15–20 cm	the procrustes analysis method
	[12]	—	about 2 m	inertial sensing data can add more reliable tracking capabilities
	[13]	RF: 4.75 m SVM: 4.76 m RADAR: 4.85 m	1.64 m	SVM is used to interpolate expected RSS at non-site-surveyed positions
	[14]	5.3 m	<2 m	accelerometer data+5 GHz frequency band
	[15, 16]	NBC: 2.438 m WKNN: 1.452 m	RGDC-N: 1.46 m RGDC-W: 1.18 m	domain clustering
probabilistic	[17]	fingerprint: 8.2–8.4 m PL: 11–12 m	about 8 m	this document studied how to reduce database size which is reduced by 80%
	[18, 19]	—	0.5–5 cm	CFRs from multiple channels and a number of locations-of-interest
fusion technology	[20]	MLID: 80–90% WiFi: 25–35% Wang: 20–60%	90–100%	inertial sensor. Image is used as a reference for pruning
	[21]	—	0.2 m	RGB-D sensors
	[22]	PDR: 6.274 m EKF-based: 2.804 m PF-based: 2.904 m	2.166 m	stable environment and inertial sensor is necessary
	[23]	WiFi: 5.37 m PDR: 8.43 m WiFi+PDR+KF: 4.83 m WiFi+PDR+PF: 4 m	2.3 m	inertial sensors
	[24]	WiFi: 13–100% iBeacon: 16–100%	46–100%	BLE technology
	[25]	4.05 m	2.33 m	BLE technology+KNN
	[26]	WiFi: 2.525 m BLE: 2.254 m both: 2.363 m	2.55 m	BLE technology
	[27]	—	—	bluetooth receiver, optical and magnetic sensor
	[28]	office: 9.5 m market: 10 m UPL: 4 m	office: 4 m market: 3.5 m UPL: 1 m	phone collects inertial sensor readings and magnetic signals
	[29]	single signal: >1.6 m	1.6 m	magnetic data and the support of server

need to utilise other techniques known as fusion technology to improve positioning accuracy.

3.1 Range free

The implementation process of fingerprint technology is generally divided into offline phase and online phase [44]. (i) *Offline phase*: establishing a wireless map that matches the RSS value of each AP and location information in the corresponding area; (ii) *online phase*: comparing the RSS value received by the mobile receiver carried by the target with the information of the wireless map to estimate the position and the trajectory of the target. According to the ways to build a wireless map and RSS processing methods, smartphone-based indoor active location technologies can be classified as deterministic technologies and probabilistic technologies.

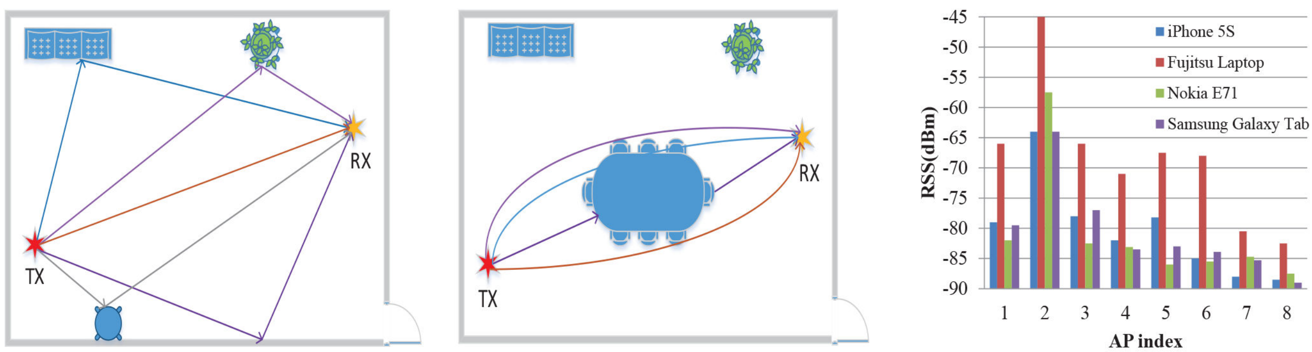
3.1.1 Deterministic: The deterministic algorithm stores the average of RSS received over a period of time as location fingerprinting information in the database. Then the system can use corresponding decision algorithms to determine the closest position after comparing location fingerprint information features and the information stored in the fingerprint database.

In order to make maximum use of the WiFi signals transmitted by APs in the region, MAPD [10], an AP deployment mechanism, is proposed to assist fingerprint-based indoor localisation. As shown in Fig. 3, they chose locations with lower positioning accuracy on the wireless maps calibrated by the pre-existing APs. Then, MAPD deploys a large number of APs in the vicinity. After combining field measurements, the minimum means position error calculation and progressive greedy search are used to determine the location and number of APs. The experimental results show that MAPD can provide higher positioning accuracy.

In the offline phase, Balzano *et al.* [11] propose a novel framework which can modify the database through multiple modules connected to the wireless sensor network. This approach allows the system to effectively update the database of collected signals in real time and automatically train the signals without any human intervention. Radio maps in LOCALI [12] are integrated using the map topology of the indoor environment to calculate the path loss of different trajectories in a complex indoor environment. Taking into account the fading effects caused by multipath propagation, environmental factor absorption and antenna

Table 2 Comparison of range-based positioning methods

Basic technique	Reference	Positioning accuracy of other algorithms	Positioning accuracy	Specific requirements
TOA/TDOA	[30]	—	—	minor silicon or firmware modifications
	[31]	20 MHz bandwidth: 4 m 40 MHz bandwidth: 2m	20 MHz: 1.5 m 40 MHz: 1m	the round-trip time and AoA
	[32]	—	4 UAV: 2 m	the UAVs
	[33]	2.37 m	about 0.75 m	the RSS and pathloss exponents estimation
	[34]	pure ToA: 0.46 m pure IMU: 0.98 m	hybrid EKF: 0.41 m hybrid PF: 0.35 m hybrid MAP: 0.31 m	IMU consists of accelerometers and gyroscopes
	[35]	—	<1.8 m	the CC1101 ultra low power radio transceivers
	[36]	RSS: blow 10.7 m TDOA: blow 9.1 m	the proposed RSS/TDOA: 7.9 m the enhanced RSS/TDOA: 6.6 m	modify hardware infrastructure. Taylor-series expansion and maximum-likelihood estimation
	[37]	—	0.06–0.26 m	the two-step least squares and unscented KF algorithm
AOA	[38]	—	3.7 m	asking the user to perform gestures when they need estimates
	[39]	DTW: 1.6–3 m Zee: 2.1–4.4 m	<1.4 m	inertial sensors. Step boundary detection, step length and orientation angle estimation
	[40]	—	—	single AP with multiple antennas
	[41]	SpotFi: 2.61 m ArrayTrack: 3.52 m	0.91 m	phased array with smart signal processing on APs
FDOA	[42]	WLS: blow than 0.4 m NLOS technology: 0.35–1 m	0.05–0.4 m	the instrumental variable technique is used to compensate the estimation error of the estimated target velocity
	[43]	—	—	4D cross ambiguity function (CAF)



a *b* *c*

Fig. 2 *Challenges for indoor positioning*
(a) Multipath effect, *(b)* Blocking obstacles, *(c)* Device heterogeneity

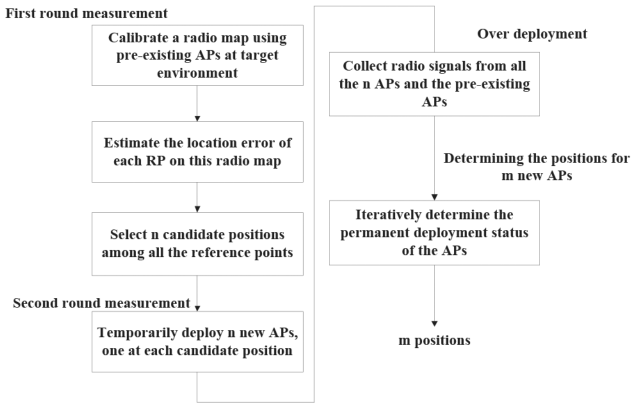


Fig. 3 *AP deployment mechanism*

alignment changes, LOCALI uses map overlay technology to estimate the target position instead of triangulation. For the impact of device heterogeneity (Fig. 2*c*), Zou *et al*. [12] apply the Procrustes analysis method to transform the WiFi RSSs to a new type of standard location fingerprints. The system uses the weighted *k*-nearest neighbours and indoor positioning algorithms based on the standardised location fingerprints to improve system robustness. Experimental results show that using standard location fingerprints has a good effect on reducing device heterogeneity.

In the online phase, Some scholars have used other methods to reduce the dependence of fingerprint-based indoor WiFi positioning systems on radio maps in order to reduce the workload of field investigations in the offline phase. For instance, Hernández *et al*. [13] introduce a vector regression model which can estimate the RSS of unmeasured locations using nearby measured RSS. In the process of estimating the RSS of the unmeasured location, a continuous space estimator is developed that uses a support vector regression algorithm to estimate virtual fingerprints that are not available in the fingerprint database, to overwrite the unsaved location. There are also the researches of position estimation strategies to improve the performance of WiFi-based indoor positioning technology. Plets *et al*. [14] studied the effects of different optimisation strategies on positioning results, including the previous location considered, modifying the number of WiFi scans for each location, modifying the signal band, adding accelerometer data, and adjusting the position of the phone in the body. Among them, the scheme of adding accelerometer data has the greatest impact on positioning accuracy. In addition, RGDC [15, 16] uses each of all available APs to estimate the location of the target rather than selecting a subset of APs like WKNN and NBC approaches.

3.1.2 Probabilistic: Compared with the deterministic algorithm, although the computational complexity of the probabilistic algorithm is higher, it provides higher accuracy and is very robust to noise. The probability algorithm first calculates the RSS probability distribution function for each AP received at a fixed location, and then merges these distribution functions into a joint distribution function and saves the joint distribution function as a location fingerprint in the database. Finally, when the RSS of the receiver is r_i, the algorithm searches the database to find the most probable location where the RSS is r_i.

In practice, an oversised database severely limits the development of large-scale positioning systems. Positioning systems using radio propagation path loss models tends to be less accurate than fingerprint-based positioning systems. For this reason, Talvitie *et al*. [17] propose a new concept for compressing RSS images. Although spectral compression can reduce the size of RSS image information, there is still measurement noise and shadow noise in these data. At last, the method discards the excess noise based on the correlation between neighbouring measurements of APs and retains valid transform-domain components. The experimental results show that the database of the system is reduced by 80% without affecting performance. Alfakih and Keche [45] proposed an enhanced positioning method based on the nearest neighbour algorithm. To reduce the positioning errors, the set of the RSS samples collected from several APs was used rather than their average. In [18, 19], the authors propose a positioning system with centimeter-level accuracy in the case of NLOS. In order to improve accuracy and reduce environmental interference, the system needs to process channel frequency response (CFR) collected in the positioning area when the fingerprint database is created offline: the CFRs in different channels are combined and stored in the fingerprint database. In the online phase, the system also compares the received CFR processing value with the fingerprint database and uses time reversal technology to achieve positioning. Results of the experiment demonstrate the accuracy can reach centimeter level in a typical office environment with large effective bandwidth.

3.1.3 Fusion technology: As we all know, smartphones contain many functional modules, including WiFi, bluetooth, cameras and so on. A great deal of research combining WiFi and other functional modules has been used for indoor positioning based on smartphones. In addition, we can also use the integration of other devices and the smartphone to achieve indoor positioning. In this section, the fusion technology of converged WiFi and other technologies will be introduced to improve system performance [46, 47].

With visual: as a research hot spot in indoor positioning technologies, computer vision [48, 49] can be realised by using a camera module on a smartphone or other camera equipment. Environmental features by analysing photographs or videos can be saved directly to the database [50, 51]. These features can also be synthesised into a three-dimensional (3D) map of the indoor environment.

Although indoor positioning systems using only images can achieve good accuracy [52], they are susceptible to interference from obstacles and can only be used in the LOS. Visual-based indoor positioning by combining WiFi can not only achieve higher accuracy than the original method but also increase the coverage of the positioning system. Jiang and Yin [20] consider that when the database is large, indoor positioning based on image matching is difficult to achieve accurate positioning because of the similar decorative style of the building. On the other hand, the cost of the query will also rise due to the huge database. For reducing the query cost, the system first divides the indoor area according to indoor original WiFi signal strength. After receiving the WIFI signal and visual information corresponding to the target location, the system clusters the reference images in the same area and deletes the impossible images. This multi-level serial positioning mode greatly improves the accuracy and efficiency of the algorithm. Fig. 4*a* provides a signal tree based on WiFi and visual signals. There is another fusion technology of WiFi and visual signals for pedestrian tracking in [53]. Compared with the serial combination of WiFi signals and images in [20], Dao *et al*. [53] use a WiFi positioning system and a visual-based positioning system to achieve positioning, and then fuse the positioning results of the two systems. The experimental data show that the proposed fusion method has better tracking results than the single-signal-based method. Similar to [53], Duque *et al*. [21] combine WiFi positioning system with depth maps. In the WiFi positioning system, a smartphone collects the WiFi RSS transmitted by multiple surrounding APs and sends the RSS to the processor. The system then uses RGB-D sensors to obtain indoor scene depth maps to identify the human body and provide more accurate positioning results.

With inertial sensors: accelerometers and gyroscopes embedded in existing smartphones can basically meet the requirements of indoor inertial navigation. It is noteworthy that positioning errors of inertial navigation technologies will continue to accumulate over time, thus other technologies can be combined to constantly revise positioning results. Due to space limitations, this section will introduce indoor positioning systems with inertial navigation and WiFi technology.

Guan and Zhang [54] develop a corresponding client application program which obtains the signal strength values of the surrounding WiFi by WiFi modules, and gets the process of

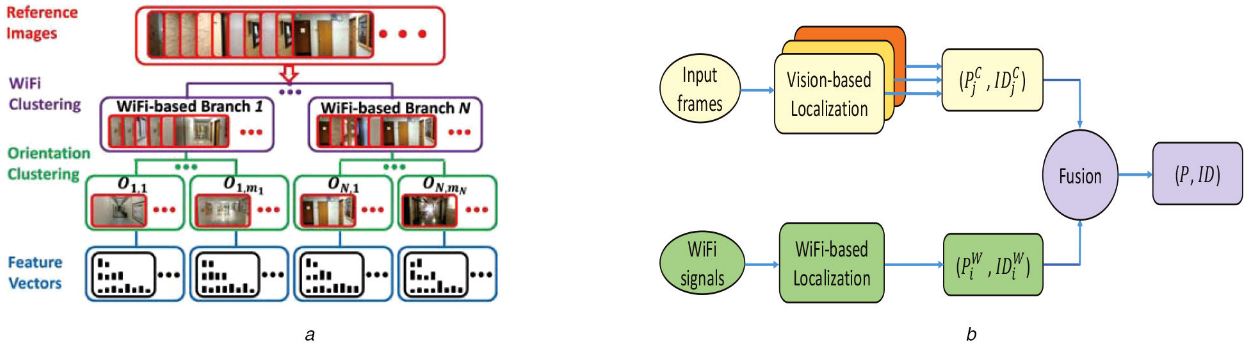


Fig. 4 *Two combination modes of different signal processing methods*
(a) Serial mode, ***(b)*** Parallel mode

walking and the number of steps by orientation sensor and acceleration sensor. In this typical hybrid indoor positioning system, WiFi positioning technology is used for preliminary positioning, and then more accurate positioning results rely on inertial sensor positioning technology. Although the idea of using this fusion positioning has achieved good technical results, many details need to be paid attention to during the research process. For example, LaP [22] makes a breakthrough in restrictions such as a large number of calculations and inconvenient real-time use. After referring to changes in WiFi signal strength and map information, LaP sets different indoor landmarks in some special locations. Hence, the system can use these landmarks to correct the cumulative positioning error of the PDR algorithm without the fingerprint database. KAGF [23] conducts relevant research in improving the efficiency and accuracy of indoor positioning systems, such as modifying irregular paths that appear in consecutive positioning results. KAGF system uses the maximum likelihood algorithm to automatically obtain the user's initial location information and direction of movement. The combination of the Kalman filter (KF) and auto-adaptive dynamic grid filter (GF) is used to process the result of WiFi and the PDR system to reduce system errors and processing time. The final result shows that the system has better accuracy and computational complexity and a longer WiFi update interval.

With bluetooth: the cost of bluetooth hardware has dropped to a reasonable price and bluetooth has been widely used in mobile phones or computers. Bluetooth-based positioning technology has received widespread attention. Although both bluetooth and WiFi operate at 2.4 GHz, there is no mutual interference between the two signals. Therefore, the positioning system combining WiFi and bluetooth technology is designed to achieve complementary advantages.

Chiu *et al*. [24] propose a hybrid system assisted by the RSS fingerprint to reduce the impact on indoor accuracy due to indoor signal interference. The system operates as follows: the WiFi signal estimates the approximate location of targets by dividing indoor space. The bluetooth signals are used to accurately locate the target location. The experimental results show that the system can be well applied in complex indoor environments. i-KNN [25] analyses the proximity of RSS fingerprints and BLE devices to filter out most fingerprints that do not meet the proximity requirements. In this way, i-KNN can use the subset of the fingerprint database corresponding to the user to achieve positioning. This method not only helps the system to achieve rapid positioning but also improves positioning accuracy. There are also some studies on fingerprint positioning based on WiFi and bluetooth integration. For example, Miyashita *et al*. [26] propose a WiFi-BLE fusion location system that uses a multi-layer perceptron as a fusion classifier, rather than a system that generates a wireless map using only WiFi signals. The system in [27] creates 3D fingerprint database based on the RSS of WiFi and bluetooth, and the fusion of optical sensor 3D coordinate and magnetic sensor rotational attributes. The system accuracy is also significantly improved with multiple input signals in the laboratory.

With geomagnetic: except for some special places, the distribution of geomagnetism is almost distributed in any space around the earth. The magnetic flux distribution of the geomagnetic field is different in different positions. Therefore, it is another method to positioning indoor by using the WiFi signal combined with the continuously changing magnetic signal. The use of geomagnetism in indoor positioning has to face the problem of noise direction induction caused by abnormal magnetic fields of building materials. In order to solve above challenges, Magicol [28] first uses Step-Based Vectorisation to improve the discriminability of indoor geomagnetic signals and then uses a two-pass bidirectional particle filtering process to fuse geomagnetic signals and WiFi signals to further improve the positioning accuracy. Guo *et al*. [29] design WiMag which consists of a magnetic positioning system, a WiFi positioning system and a PDR system. According to the state of the target, WiMag can select the optimal fusion strategy by particle filter after analysing the positioning accuracy, real-time performance, coverage and cost. This multi-mode fusion positioning system outperforms all single indoor positioning techniques in terms of positioning accuracy and robustness. The system also has the advantages of high precision, low cost and wide coverage in complex indoor scenes.

3.2 Range-based

As shown in Fig. 1 in Section 2, this section introduces methods related to range-based indoor positioning algorithms.

3.2.1 Time of arrival (TOA)/time difference of arrival (TDOA): As a method that extracts information from the signal arrival time to achieve positioning, the estimation of signal arrival time delay is a major factor affecting the positioning accuracy. Due to multipath interference, NLOS, noise and the time synchronisation between indoor devices, many current research on TOA or TDOA have proposed improved algorithms based on existing problems. Figs. 5*a* and *b* show the setting of the indoor positioning system based on TOA and TDOA, respectively.

Time of arrival: in terms of cost, back in 2007, Golden and Bateman [30] discuss a novel TOA approach developed by Intel and make a breakthrough in delivering significant performance through concerning how to get the best possible location performance with minor modifications to existing WLAN communication systems (software and(or) hardware). In 2015, Yang and Shao [31] proposed a WiFi positioning technology which uses a mechanism for transmitting multiple predefined messages to improve the positioning performance of TOA or angle of arrival (AOA). As mentioned in the paper, this mechanism allows the system to reduce the need for bandwidth and antennas while maintaining high-precision performance. For reducing the number of anchor nodes, Danjo *et al*. [32] achieve indoor positioning on the use of the unmanned aerial vehicle (UAV). The principle of reducing costs by using UAVs for positioning is that UAVs can collect and send signals to targets by moving their own positions. Without increasing the number of anchor nodes, a small number of UAVs can meet the positioning requirements of systems. In actual implementation, the position of the UAV is estimated by GPS, so there is an error in using the UAVs as anchor nodes. When communication between the UAV and the target is in the NLOS condition, positioning accuracy will be varied affected. For this reason, the author used the perturbation method to analyse the

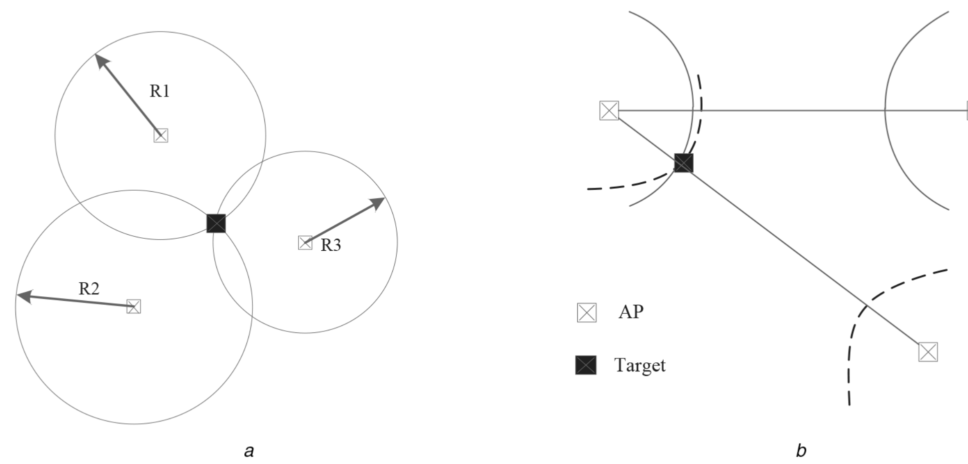


Fig. 5 *The setting of the indoor positioning system based on TOA and TDOA*
(a) TOA, ***(b)*** TDOA

relationship between the above error and positioning error to improve positioning performance.

When communication between the UAV and the target is in the NLOS condition, positioning accuracy of systems will be greatly affected. In the case of serious NLOS effects, Li *et al*. [33] propose a method by utilising both TOA and RSS measurements. Their purpose is to analyse the difference between TOA and RSS geometric area to obtain an optimised range of data. Then, these data are introduced into the triangular centroid algorithm to achieve positioning. The simulation results show that the algorithm has better performance and higher positioning accuracy than the traditional algorithm in reducing the error caused by the NLOS effect. There are also other methods proposed to improve the accuracy of locating a moving object indoors, such as the TOA/IMU indoor positioning system [34]. Soltanaghaei *et al*. [55] propose MonoLoco, a decimeter-level WiFi localisation system, which uses multipath triangulation technology. Multipath reflections are used to enhance positioning rather than being discarded and the orientation of the target relative to the AP is determined.

Time difference of arrival: the accuracy of TOA/TDOA depends on the exact time synchronisation between APs and mobile devices. TOA uses the absolute time at which the signal reaches APs to determine the location of the mobile device, but there are usually errors in the absolute time collected. For reducing the requirement of system time synchronisation, TDOA utilises the time difference between signals arriving at multiple APs to achieve positioning. The time synchronisation between different measurement devices is mainly accomplished by recording the signal arrival time offset. In the actual measurement process, the signal arrival time offset also needs to compensate for the time difference of transmitted signals.

Nawaz *et al*. [35] propose a positioning system using three TDOA measurement units. The system demodulates the obtained time difference pulses received by the measurement unit to reduce the impact of clock jitter. The positioning is then achieved by combining the voltage level corresponding to the time difference mapped to the distance difference. The experimental results show that the system requires less time synchronisation than the traditional TDOA positioning system in 2D space. Türkoral *et al*. [56] introduce Swarm robotics for WiFi-based indoor positioning. The system deploys robotics with WiFi communication function in the corresponding area, and then uses TDOA and RSSI positioning methods to estimate the location separately. The final positioning result is obtained by setting certain weights on the positioning results of TDOA and RSSI. There are other similar studies. Kumarasiri *et al*. [36] present a hybrid indoor positioning algorithm based on RSSI and TDOA measurements. By combining TDOA and RSSI methods, the system has good performance in terms of positioning accuracy, algorithm complexity, convergence time and energy consumption. The algorithm proposed by Wang *et al*. [37] can adaptively analyse NLOS/LOS conditions and obtain accurate positioning results by using two-step least squares and untracked KF algorithms.

3.2.2 Angle of arrival: In the implementation of the AOA algorithm, at least two APs are required to receive the signal sent by the mobile terminal. Therefore, it is easy to obtain the lines between APs and the mobile terminal by the incident angle of the signal and the position of APs. The easiest way is to use the intersection of these lines to determine the location of the mobile terminal. Gallo and Mangione [38] propose to calculate the arrival angle of the smartphone signal and the movement of the smartphone by associating the measured WiFi RSSI with electronic compass data on the smartphone. This type of system only requires smartphones to receive signals and APs to transmit signals for positioning. It has certain advantages in terms of system cost and the protection of user privacy. Even under severe multipath conditions, initial results can also accurately estimate the arrival angle. The ISWF [39] combines inertial sensors and AOA-based WiFi fingerprints for positioning. This method effectively avoids inaccurate positioning results caused by the swing of the smartphone under the condition that only the AOA signal is used.

As with TOA/TDOA, positioning accuracy of AOA is susceptible to environmental change such as noise, multipath effects and NLOS. In [40], an indoor AOA estimation algorithm using the single AP with multiple antennas is proposed to deal with these problems. The system first uses an auto-focus method to obtain a coherent combination matrix of subcarrier frequencies. By using this matrix, the system can decorrelate the received multipath signal in the spatial domain. Regardless of whether the multipath correlation between the signals is high or low, simulation results of the system all have a good performance. The low signal-to-noise ratio in the indoor environment will also significantly affect the positioning accuracy of the AOA method. ROArray [41] is proposed to improve the anti noise ability of the system by performing coherent estimations in space, time, and frequency. The experimental result shows that the positioning accuracy of ROArray is significantly higher than other solutions.

3.2.3 Frequency difference of arrival (FDOA): In the positioning process, the FDOA mainly uses the speed information of the moving target. Due to the relative speed between the AP and the receiver, the frequency and phase of the signal received by the receiver may change with the Doppler effect. The relative speed between the AP and the receiver indoors is small, thus using FDOA for indoor positioning is a challenge. To solve this problem, Yong *et al*. [42] combine TDOA and FDOA measurements to propose a method for positioning the low-speed moving target. According to the introduction in [42], the position information of two APs near the target is first obtained by NLOS technology, and then this position information is used to estimate the target position and heading angle. The system estimates the angular velocity and linear velocity of the target on the assumption that the target is

Table 3 Performance indicators (accuracy, complexity, extensibility, cost

Indicators	0	1	2	3	4	5
accuracy	>10 m	3–10 m	1.2–3 m	0.5–1.2 m	0.1–0.5 m	0–0.1 m
complexity	>4 s	1.8–4 s	1–1.8 s	0.5–1 s	0.2–0.5 s	0–0.2 s
extensibility	<10 m^2	10–100 m^2	100–500 m^2	500–1000 m^2	1000–3000 m^2	>3000m^2
Cost	very high	high	above medium	below medium	low	very low

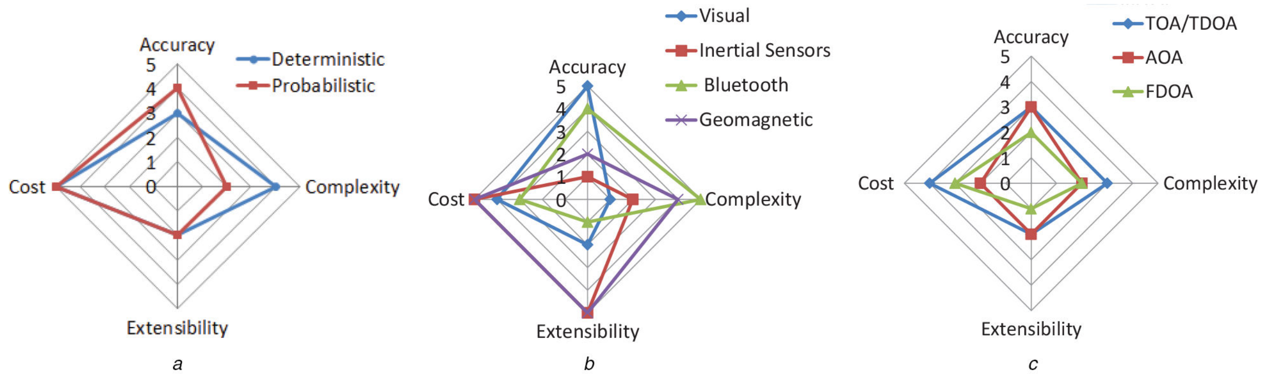


Fig. 6 *Performance comparison of all recent active positioning systems*
(a) Deterministic, probabilistic, ***(b)*** Visual, inertial sensors, bluetooth, geomagnetic, ***(c)*** TOA/TDOA, AOA, FDOA

uniform. Finally, the instrumental variable technique is used to compensate for the estimation error of the target speed. Watson and Mcelwain [43] use a set of distributed sensors to capture and distribute compressed sample data to perform 4D CAF, i.e. TDOA, FDOA, FRDOA, and cyclic stationary features extracted through spectral correlation function to uniquely identify, categorise, relocate and track each emitter. Although it is still difficult to indoor positioning using FDOA alone, it provides new ideas for future research.

3.3 Performance comparison

By describing the above different methods, the active positioning algorithms are classified into two categories in Section 3: ranging-free and ranging-based algorithms. Although similar performance in the process is summarised in the same category, there are still differences in the positioning methods for different basic techniques. In particular, the evaluation of accuracy, cost, extensibility and complexity can better reflect the differences between different positioning methods. Table 3 shows the corresponding evaluation criteria, which are divided into six levels. As shown in Fig. 6, each radar chart consists of four directional axes that indicate different classification criteria. Correspondingly, there are six different levels for different standards. 0 corresponds to the innermost layer and 5 corresponds to the outermost layer. The higher the standard value, the better the corresponding performance. The comparison presented in Fig. 6 is the performance comparison, not the specific value.

Positioning accuracy is the primary indicator to measure the performance of different indoor positioning techniques. It reflects the closeness between the location estimated by the positioning method and the actual location. In the past decade, the upgrade of related hardware and software has reduced the limitations of other factors on system accuracy. Positioning accuracy is measured in kilometers, meters and even centimeters. Hence, the highest positioning accuracy is set to <0.1 m, and the lowest accuracy evaluation standard is 10 m or more.

Cost will directly affect the application and popularisation of positioning algorithms. Exorbitant costs make it difficult to guarantee the feasibility of the system. According to the contents mentioned in Section 2, system costs are affected by the following conditions: performance requirements, operating environment, hardware devices, system maintenance and expansion. In addition to some special-purpose indoor positioning systems, the evaluation criteria for cost can be divided into six levels as shown in Table 3.

Scalability is the ability of the system to adapt to changes in the environment based on system performance, cost and maintainability. On the other hand, scalability can also be considered as a decisive factor in the coverage of positioning systems. In view of the factors of signal or infrastructure, the effective coverage of a system changed from $< 10\,m^2$ to $> 0.1\,km^2$.

Complexity of the system can be evaluated from time complexity and space complexity. The lower the time-consuming of positioning technology, the higher the real-time performance. And the space complexity is a manifestation of the system resources occupied by the positioning technology. Although time complexity and space complexity often influence each other, positioning systems with superior performance can balance the effects of the two. The complexity criteria can be divided into six levels, as shown in Table 3.

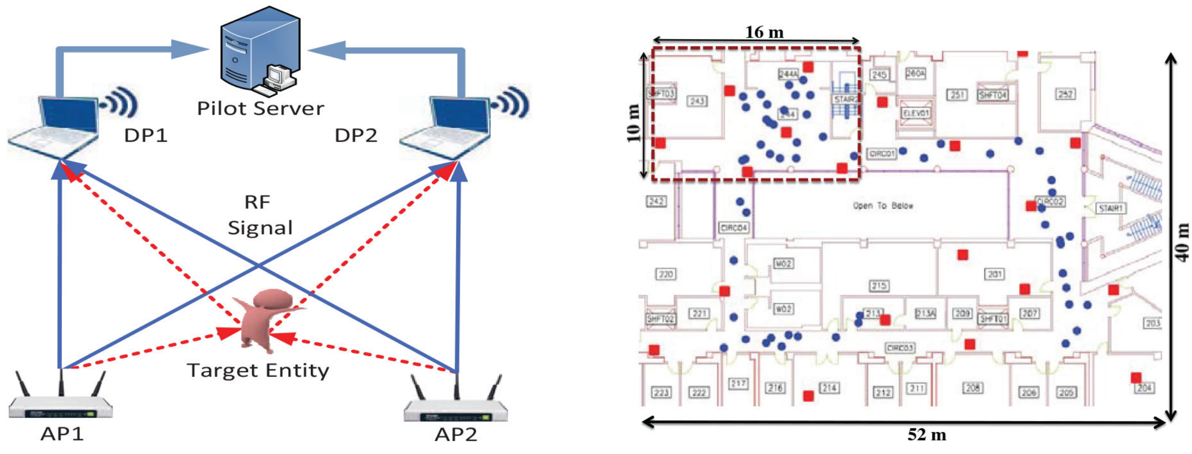
4 Passive positioning

Research on indoor active positioning has become increasingly mature and been widely used. People can enjoy good ILBSs as long as they carry specific smartphones or dedicated devices. However, in many specific occasions, indoor active positioning cannot be used well, such as remote monitoring for the elderly safety, real-time positioning of criminals and so on. In order to compensate for the lack of the indoor active positioning, passive positioning can help people achieve ILBSs without relying on specific equipment.

4.1 RSSI based

It is a passive positioning method to monitor people in buildings directly using the change of WiFi signal strength. At present, researches on RSSI-based indoor passive location include human detection and tracking. This paper first give a few examples of researches on human detection. Schafermeyer *et al.* [57] research how to identify individuals using simple wall-mounted RF transceivers and IR sensors with fingerprinting techniques. In this process, the RF signals between the four transceivers and Gaussian mixture model are used to classify the monitoring people. In order to detect the mobility of people, Ma *et al.* [58] propose a method based on WiFi signals to recognise behaviours and movements of people in the building. The frame of this method is divided into data preprocessing, time slice processing and two-level classification.

In terms of human tracking, a typical passive positioning infrastructure includes APs and monitoring points (MPs). MPs detect WiFi signal changes from APs to passively locate people. For instance, Alkandari *et al.* [59] uses 1 AP and 1 MP to estimate the speed of motion in an indoor environment. Similar to [59], 1



a b

Fig. 7 *Experimental deployment of positioning system based on CSI amplitude*
(a) FIMD, ***(b)*** SpotFi

MP is also added for experiments to provide better performance in [60]. In other studies, Oguntala *et al*. [61] use the ranging method of passive RFID receiving signal strength to achieve personnel positioning. The particle filter algorithm analyses and calculates RSSI to get the target position in the indoor environment. Although these systems can use RSSI changes to locate people, Xu *et al*. [62] find that slight changes in the indoor environment can also affect the WiFi transmission. To solve such problems, the probabilistic classification method based on discriminant analysis is applied to the fingerprint-based recognition algorithm. At the same time, in order to reduce the errors caused by multipath effects and make the classification algorithm have better classification results, the signal is transmitted at the frequency of 433.1 MHz instead of 909.1 MHz.

4.2 Channel state information (CSI) based

In the past, how to measure the precision of wireless channel has become a biggest factor limiting the extensive research on CSI. But since 2010, researchers modified the firmware to make it possible to obtain a sample version of CFR in the form of CSI using an ordinary wireless network card. Compared with RSSI, CSI can obtain the frequency response of each subcarrier and provide fine-grained CSI. CSI includes the amplitude and phase information of each subcarrier which provides abundant information in the frequency domain. In this section, we describe indoor passive positioning techniques by utilising amplitude or phase information of CSI, respectively.

4.2.1 Amplitude: The reason why RSSI-based distance estimation lacks stability and reliability is that the result of RSSI measurement is affected by multipath effects. For reducing the multipath effects in the above signal propagation, FIMD [63] uses a novel feature extracted from CSI to leverage its temporal stability and frequency diversity. The motion detection is implemented using density-based spatial clustering of applications with noise algorithm to identify outliers from normal features in continuous monitoring. In addition the false alert filter and data fusion schemes are used to improve the detection accuracy. Fig. 7*a* shows the deployment of FIMD. FILA [64] is proposed to leverage CSI to mitigate the multi-path effect at the receiver. CSI has been proved to be effective in indoor positioning by using only the simplest trilateration method. LiFS [65] considers a problem: even the fine-grained CSI can not be easily modelled in some rich multipath propagation indoors. It is also a fact that not all subcarriers are affected equally by multipath reflections, the subcarriers that are not affected by multipath are identified in the pre-processing process. For reducing costs, Kotaru *et al*. [66] present the design and implementation of SpotFi which is deployed on commercial facilities as shown in Fig. 7*b*. SpotFi contains two key innovations. One is to accurately calculate the multipath component of AOA by making use of super-resolution algorithms, and the other is to identify AoA of direct paths between the target and APs by filtering and estimation techniques. The positioning results of SpotFi show SpotFi is comparable in accuracy to the latest positioning systems with large antenna arrays that are not suitable for widespread deployment. Abdel-Nasser [67] propose MonoPHY, a device-free WLAN-based localisation system, which uses a single wireless stream. This CSI data for each position is modelled as Gaussian mixtures and stored in the fingerprint. Xie *et al*. [68] introduce mD-Track, a device-free Wi-Fi tracking system. This system can jointly fuse information from as many signal dimensions as possible, such as AOA, TOF, Doppler shift, etc., to overcome the resolution limit of each individual dimension. mDTrack achieves finer resolution without requiring a wider frequency bandwidth or a larger number of antennas. Qian *et al*. [69] present Widar, a WiFi-based passive tracking system. Widar estimates the user's moving velocity (both speed and direction) and position at a decimeter level. It establishes a theoretical model that geometrically quantifies the relationship between CSI data and the user's position and moving velocity.

In addition to trilateral positioning algorithms, fingerprint-based methods are also used for CSI, such as DeepFi [70]. The implementation of DeepFi is as follows: in the offline training phase, DeepFi's fingerprints are generated by all weights obtained by deep learning. In the online localisation phase, the system utilises a probabilistic method based on radial basis function to estimate the position of the target. Xiao *et al*. [71] propose a new positioning method that makes better use of the frequency diversity with different subcarriers and spatial diversity with multiple antennas. Then the similarity between different fingerprints is calculated by the Kullback–Laibler divergence to match position. Xiao *et al*. [72] design a necessary anomaly detection block as a positioning trigger relying on the CSI feature shift when the target emerges. Afterwards, a probabilistic algorithm is proposed to match the abnormal CSI with the fingerprint database to estimate the position.

4.2.2 Phase: At present, most CSI-based indoor passive positioning methods use only the amplitude information for positioning, and research on the use of CSI phase information for positioning has just begun. It is difficult to achieve positioning by only using phase information, but there are still a number of related studies that have been proposed. In [73, 74], there are some remarkable research results in this field. CSI phase information is used for indoor fingerprinting and the feasibility of utilising the calibrated phase information of CSI for indoor positioning is proved. A deep network with three hidden layers is used to train the calibrated phase data and a probabilistic method based on the radial basis function is utilised for online location estimation. Similarly, Wang *et al*. [75] extract the CSI phase information after getting new CSI AOA images. Combined with the deep convolutional network, ideal positioning results can be obtained in the room with commercial 5 GHz WiFi. Another idea is to infer the

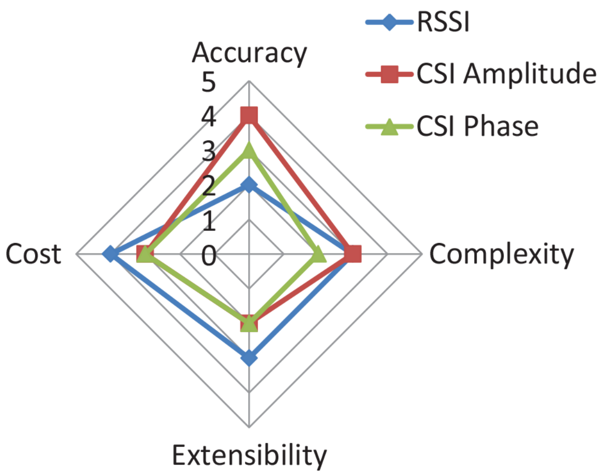


Fig. 8 *Performance comparison of all recent passive positioning systems*

path of movement by analysing signal changes caused by the object motion. For example, WiDir [76] infer the walking direction after analysing the dynamic phase changes from multiple WiFi subcarriers. The system applies multi-dimensional Fresnel zone space which can be naturally formed by WiFi devices to improve scalability.

4.3 Performance comparison

In this section, a performance comparison conclusion of the above-mentioned WiFi-based passive indoor positioning techniques is provided. Fig. 8 shows a radar chart of the performance of different classifications of positioning methods. The application and evaluation criteria for performance in Fig. 8 are the same as those for active indoor positioning techniques. The comparison presented in Fig. 8 is the performance comparison, not the specific value. However, some systems do not directly mention partial performance experimental results and only give ambiguous results. We can refer these results to the standards we need.

The comparison chart provided can be used as a reference for selecting a suitable localisation scheme for a specific application scenario. In the next section, several open research issues for both active and passive indoor positioning techniques base on WiFi will be provided.

5 Open research issues about WiFi positioning

The importance of the ILBS is well known and its applications are becoming more and more widespread. Although the related techniques are relatively matured, there are still many difficult challenges to be solved in implementing the indoor positioning system. In addition to some of the same challenges, the problems faced by different technical solutions are also different. This section will describe these challenges in both active and passive positioning techniques.

5.1 Active

5.1.1 Map construction: During the training phase, fingerprint-based indoor positioning methods determine the RSSI features in the positioning area by drawing a wireless map. However, the current wireless map is mainly drawn by humans to complete the construction. Due to the need for signal acquisition at various locations, the job of constructing this map is time-consuming and labour-intensive. However, the indoor environment changes frequently, thus many maps have not a long life cycle. Frequently updating the map poses a challenge to cost, robustness and scalability of the system. In the latest work, it is proposed to use crowd-sourced data and magnetic sequence similarity to complete the construction of indoor WiFi maps, and there are many other studies are ongoing.

5.1.2 Application limitations: Unlike GPS and other outdoor positioning techniques, the infrastructure related to indoor positioning techniques has not been widely deployed. One of the important reasons is that ILBSs are not widely available. although some sites have deployed WiFi infrastructures, the original intention of deploying these devices is not intended for the indoor location. In addition, the location and working method of these devices will also affect the performance of indoor positioning techniques. In fact, some methods have been proposed to use these infrastructures to improve accuracy and other performance. For example, the MAPD [9] in Section 2.2.1 first considers using existing APs to generate radio maps.

5.1.3 Personalised service: Currently, most ILBSs are intended to provide high-precision positioning. In the room, high-precision ILBSs have a significant advantage, but in order to obtain high accuracy, other performance often needs to be compromised. In some cases, when the user's demand for accuracy is not high, excessive resource caused by too high precision will be wasted. Hence, in the process of designing the indoor positioning precision system, the optimal solution is achieved by fully considering the requirements of accuracy, cost, real-time and reliability of different application scenarios.

5.2 Passive

5.2.1 Positioning in the unknown environment: At present, most passive positioning techniques are used in familiar environments. First, a series of infrastructures should be deployed, and then the features are extracted from the WiFi signal during the training phase. Finally, the corresponding models are established by these signal features to achieve positioning. When the application scenario is unknown, such as encountering earthquake, fire, anti-terrorism and other emergencies, it is not impossible by using this approach to achieve positioning.

5.2.2 Interference: In order to avoid noise interference to get the desired result, the system is often carried out in a specific environment when researchers study the passive indoor positioning technology. If the indoor passive positioning method is applied in a real environment, noise interference is unavoidable, such as an unrelated human. TinySense [77] solves the challenges of detecting the interaction of multiple people breathing by filtering out non-compliant CSI in human health monitoring. In terms of indoor positioning, radio tomographic imaging (RTI) has received great attention in reducing the limitations of indoor layout and noise. In the related field, three state-of-the-art RTI algorithms are introduced and their performances are compared. In a challenging situation, it is worth studying to deal with noise to improve positioning accuracy.

5.2.3 Multi-object positioning: The main difficulties of multi-object positioning are as follows: each positioning target will affect the change of the WiFi signal characteristics and the system using the subcarriers of the WiFi signal to face the same difficulty. Thus, compared to the positioning of a single object, it is more difficult to achieve multi-object positioning.

6 Summary

In the development of wireless information technology, extensive research and attention have made ILBSs more and more perfect. Indoor positioning is an important part of ILBSs. At present, for various indoor application scenarios, a large number of indoor positioning techniques have been proposed to improve system performance as much as possible. The WiFi-based indoor positioning technology has been widely researched due to low cost, widespread availability, high applicability, and so on. In this paper, WiFi-based indoor positioning techniques are divided into active positioning and passive positioning based on whether the target carries certain devices. furthermore, we analyse and categorise the latest research results and provide current unresolved issues and trends regarding WiFi-based indoor positioning techniques.

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