Indoor Intelligent Fingerprint-Based Localization: Principles, Approaches and Challenges

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***Abstract*—With the rapid development of Internet of Things (IoT) technology, location-based services have been widely applied in the construction of smart cities. Satellite-based location services have been utilized in outdoor environments, but they are not suitable for indoor technology due to the absence of global positioning system (GPS) signal. Therefore, many indoor localization technologies and systems have emerged by utilizing many other signals. In particular, fingerprinting localization has recently garnered attention because its promising performance. In this work, we aim to study recent indoor localization technologies and systems based on various fingerprints, which use machine learning and intelligent algorithms. We also present the architecture of intelligent localization. The development of indoor localization technology should have the ability of self-adaptation and self-learning in the future. And the architecture shows how to make localization become more "smart" by advanced techniques. The state-of-the-art localization systems' working principles are summarized and compared in terms of their localization accuracy, latency, energy consumption, complexity, and robustness. We also discuss the challenges of existing indoor localization technologies, potential solutions to these challenges, and possible improvement measures.**

***Index Terms*—Internet of Things, intelligent localization, fingerprint, machine learning.**

I. INTRODUCTION

UTILIZING intelligent terminals to obtain user locations, location-aware computing and location-based services (LBS) have greatly changed people's lifestyles [1]. LBS refers to value-added services that obtain user geographical locations through positioning algorithms and provide users with corresponding services on the relevant system platform, which provides location information [2]. For example, users employ smartphones to hail taxis, order food, or find parking spaces. Localization covers almost all aspects of people's needs in life [3]. According to different application scenarios and requirements, localization technologies can be divided into outdoor and indoor localization [4]. Outdoor localization and navigation technology (represented by GPS) has been widely used in people's everyday lives, in such applications as Google Earth, which could meet most of the positioning needs [5], [6]. However, owing to complex indoor environmental factors, traditional outdoor positioning technology cannot be applied to indoor positioning [7]. Therefore, determining how to quickly and accurately conduct indoor positioning has become an area of active research [8]. Indoor positioning technology is also an important research direction for future smart cities and the IoT [2], [9]–[12].

Currently, the existing indoor localization algorithms can be broadly divided into geometric distance measurement and signal strength matching methods. In detail, the former methods include Time of Arrival (ToA), Time Difference of Arrival (TDoA), and Angle of Arrival (AoA) [13]. ToA and TDoA are positioning technologies based on wireless signal transmission time. Both of them need to know the location of at least three base stations in the positioning stage, and both have higher requirements for time synchronization, which are not easy to achieve [14]. AoA involves the measurement of the incident angle of a wireless signal, and the receiver must have a directional antenna array. Because of complex indoor environments (such as personnel flow and signal interference), measurement becomes extremely difficult. The latter methods include the propagation loss model method and position fingerprint method. Similarly, it is difficult to establish an appropriate propagation model to estimate the relationship between distance and signal strength, owing to the multipath effect [15]. The position fingerprint method does not need to know the position of the base station, nor does it need to measure the time and angle, both of which increase its feasibility for indoor deployment. It has the characteristics of easy realization, easy measurement, and low cost, and has gradually become the mainstream trend of indoor positioning technology [16], [17].

The position fingerprint method is intelligent; it makes full use of the multipath effect and dependence on environmental factors, and matches the position fingerprint to obtain the location through the establishment of a fingerprint database [18]. It

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TABLE I
ABBREVIATIONS USED IN THIS PAPER

Definition	Acronym
Access Points	AP
Angle of Arrival	AoA
Artificial Neural Network	ANN
Back Propagation	BP
Bluetooth Low Energy	BLE
Broad Learning System	BLS
Building Information Model	BIM
Channel State Information	CSI
Density-Based Spatial Clustering of Applications with Noise	DBSCAN
Differential Evolution Algorithm	DEA
Dynamic Time Warping	DTW
Extreme Learning Machine	ELM
Genetic Algorithm	GA
Global Positioning System	GPS
Infrared Ray	IR
K Nearest Neighbor	KNN
Kalman Filter	KF
Kernel Principal Component Analysis	KPCA
Light Emitting Diode	LED
Location-Based Services	LBS
Mean Square Error	MSE
Network Interface Card	NIC
non Line-of-Sight	nLoS
Orthogonal Frequency Division Multiplexing	OFDM
Particle Swarm Optimization	PSO
Radial Basis Function	RBF
Radio Frequency	RF
Radio Frequency Identification	RFID
Restricted Boltzmann Machine	RBM
Received Signal Strength Indicator	RSSI
Simulated Annealing Algorithm	SAA
Support Vector Machine	SVM
Time Difference of Arrival	TDoA
Time of Arrival	ToA
Ultra Wideband	UWB
Visible Light Communication	VLC

avoids the errors inherent in measuring distance and effectively improves the localization accuracy. It can also flexibly adapt to the positioning accuracy of the application scene according to the size of the position fingerprint database [19]. Therefore, intelligent localization should have the self-adaptive and self-learning characteristics of the position fingerprint method. The core of indoor localization technology based on the field strength fingerprint is the location algorithm, which aims to find the mapping relationship between fingerprints and positions [20]. Machine learning (ML) is an effective research method of data mining in the field of artificial intelligence; it utilizes datasets to construct training models for data analysis and prediction [21], [22]. Intelligent algorithms play an important role in optimization problems [23], and both of them are widely used in location algorithms [24].

A complete overview is needed to summarize the applications of ML and intelligent algorithms in fingerprint positioning. The abbreviations used in this paper are listed in Table I. Localization technology is also an important research direction for the future smart city development of the IoT. The contributions of this work are as follows.

- We propose the architecture of intelligent localization. It consists of a terminal layer, IoT device layer, IoT cloud component layer, location strategy layer, cloud service, and location app. And the architecture is oriented to intelligent technology and has the abilities of self-adaptation and self-learning.
- We describe the implementation mechanism of indoor localization algorithms based on different types of wireless fingerprint signals, and provide detailed explanations and comparisons of the state-of-the-art in indoor localization research and development as gap for further study.
- We identify open issues for building intelligent localization based on various applications of indoor positioning technology in real life. And we also put forward the potential technology improvement methods combining broad learning, chaos theory and other interdisciplinary methods.

The rest of this paper is organized as follows. Section II summarizes the existing indoor localization reviews. We propose the architecture of intelligent localization in Section III. Section IV describes and compares the working principles of various types of wireless fingerprint signals. Section V integrates the indoor positioning technology using ML and intelligent algorithms in recent years, and expounds the implementation principles of various algorithms. The existing positioning systems are compared in detail with respect to the aspects of positioning accuracy, energy consumption, and complexity. Section VI introduces the application of indoor positioning technology in real life, including indoor location service, elderly care and personnel care, smart buildings, construction site personnel management, fire rescue, and other safety fields. Section VII summarizes the existing technical defects, presents a discussion on future research directions, and proposes the improved technical route combined with interdisciplinary methods. Finally, we draw conclusions in Section VIII.

II. THE ADVANCES OF INDOOR LOCALIZATION

Although there have been some surveys about indoor positioning technology [25], [26], [28], [30], [34], [37]–[39], the literature lacks a review report on the latest indoor localization technology and development based on fingerprint signals that utilize ML and intelligent algorithms. He and Chan [28] summarized the latest development about localization technology and systems based on WiFi fingerprints. In terms of positioning technology, it introduces how to use time or space signal modes, user collaboration, and motion sensors to locate. In terms of system deployment, we discuss the latest progress in reducing the workload of constructing a fingerprint database and calibrating heterogeneous devices for signal acquisition. The development directions of positioning technology in the future are also discussed according to the existing technology. In view of the problem of traditional wireless fingerprint location needing to pre-construct a fingerprint map of the location environment, but it not being conducive to adapt to environmental changes, Jang and Kim [25] discussed some localization methods without constructing a fingerprint map. They are classified into three categories: synchronous positioning and mapping, inner/outer extrapolation, and crowd-sourcing. Further, the accuracy, computing time, versatility, robustness, security, and participation are compared. Davidson and Piché [34] summarized the latest methods and technologies for indoor positioning with modern smartphones, and proposed that future indoor positioning technology will be accurate and reliable by integrating different types of measurement signals. Palipana *et al.* [37] mainly summarized the state of the art of localization technology based on wireless networks and radar. They presented a detailed qualitative evaluation of the respective technologies and indicated their shortcomings. They also discussed development trends and limitations. Deak *et al.* [26] gave a detailed overview of various active and passive positioning technologies developed in recent years, and compared the advantages and disadvantages of systems with respect to their wireless technology, location algorithm, accuracy, complexity, scalability, and cost.

However, the existing surveys did not discuss the techniques that can be used for indoor positioning in detail; they only compared different methods and techniques. In particular, ML algorithms are widely used in indoor location technology. Although some related reviews have summarized the applications of these methods, there is no complete understanding. For example, Sabanci *et al.* [38] simply outlined six different ML methods based on WiFi fingerprints applied to location technology, including the artificial neural network (ANN), k-nearest neighbor (KNN), decision tree, Bayesian classifier, extreme learning machine (ELM), and support vector machine (SVM). Bozkurt *et al.* [30] compared ML algorithms for indoor positioning in terms of positioning accuracy and computing time. The indoor positioning technologies of other types of wireless field intensity signals (such as Bluetooth, visible light, and magnetic field) based on ML have not been summarized, including other existing surveys. Additionally, intelligent algorithms play an important role in optimization problems, and the literature also lacks a review summarizing their applications for localization technologies. Kulkarni *et al.* [31] presented an extensive survey and a general evaluation of intelligent algorithms applications to various problems, which can address various challenges such as security, optimal deployment and data aggregation. Kuutti *et al.* [35] evaluated and compared recent vehicle localization techniques and investigates their applicability on autonomous vehicles. It also has great significance to the development of intelligent localization, especially, the low-cost systems with high accuracy and robustness. There are also abundant others related surveys, we compare them in Table II.

Among the aforementioned surveys, no review has summarized the applications of ML and intelligent algorithms for indoor localization. In this work, we investigate the intelligent localization technology according to the existing location algorithms. An architecture of intelligent localization is proposed by analyzing the characteristics of current technology, which has four layers, one service, and one app. We also discuss the applications of indoor localization in real life and the shortcomings of existing technologies, as well as potential solutions combining other multidiscipline methods in detail. We believe that this review can provide a reference for researchers and scholars and guide the future development direction of indoor positioning technology.

III. Intelligent Localization Architecture

First, we present the viewpoint of intelligent localization. That is, an adaptive localization technology without external expensive equipment that can achieve fast matching with high precision based on ML, intelligent algorithms, and other related technologies. Existing positioning technologies can be classified as active, passive, device- or mobile-based, fingerprint-based, and other aspects. In this paper, we propose a positioning framework for intelligent localization, which is oriented to intelligent technology and has the abilities of self-adaptation and self-learning. In view of the problems of the multipath effect, security, and others in localization technology, which are explained in detail in Section VII, the framework contains corresponding solutions.

We propose a four-layer intelligent localization architecture, as shown in Fig. 1, which includes a terminal layer, IoT device layer, IoT cloud component layer, and location strategy layer. In addition, it provides a cloud service and location app. First, the terminal layer senses the original data and generates the location fingerprints from the location signals, which could come from satellites, routers, access points (APs), base stations, visible light, various sensors, and other devices. These fingerprint signals are collected by devices with a variety of sensors, such as laptops and mobile phones. As there are different types of signals, a unified fingerprint database is established through data fusion technology. Next, the fingerprint database is transferred to the IoT cloud component layer by crowd-sourcing technology (reducing the time consumption), which includes local servers and cloud services. The computing power and memory of intelligent devices (local PC and servers) are limited, and they are insufficient to deal with computing tasks such as related algorithms. Therefore, cloud services are used to accomplish these tasks by using task unloading technology. The cloud services and location strategy layer are the core part of this framework, which are used to complete the model training of location algorithms and return the location result by fingerprint matching.

Cloud services mainly accomplish four types of positioning tasks: data dimension reduction, model training, regression problems, and optimizing strategies. The dimension reduction of large heterogeneous multisource datasets can find the noise data and reduce the computational complexity; hence, reducing the model training time. For the model training, we recommend utilizing a broad learning system (BLS), as mentioned previously. On the one hand, the system's characteristics match well with the positioning technology (it can deal with nonlinear problems and has high speed). On the other hand, it can also be combined with a variety of ML algorithms to reduce the model training errors and improve the positioning accuracy. For the positioning technology, ultimately it is a regression problem, which can be further processed by KNN and other algorithms. For the optimizing strategy, we contend that the intelligent algorithms are not limited to determining

TABLE II
OVERVIEW OF EXISTING RESEARCHES ON INDOOR POSITIONING TECHNOLOGY

Category	**Related works**	**Summary and Characteristics**	**Geometric**	**Fingerprint**	**ML**	**Intelligent algorithm**
IoT-based	Jiang [25]	Discussed some localization methods without constructing a fingerprint map, included synchronous positioning and mapping, inner/outer extrapolation, and crowd-sourcing.	✓			
	Deak [26]	Gave a detailed overview of various active and passive positioning technologies, compared some systems with different aspects.		✓		
	Oguntala [27]	Advocated for hybridization of techniques as an effective approach to achieve IoT-based indoor systems.	✓	✓	✓	
Signal processing	He [28]	Focused on how to use time or space signal modes, user collaboration, and motion sensors to locate.		✓	✓	
	Dardari [29]	Presented a survey on indoor wireless tracking of mobile nodes from a signal processing perspective.	✓	✓		
Mathematical methods	Bozkurt [30]	Simply compared ML algorithms and several wireless field intensity signals for indoor localization in terms of positioning accuracy and computing time.		✓	✓	
	Kulkarni [31]	Presented a general evaluation of intelligent algorithms applications to various problems which is suitable for optimal deployment and data aggregation.			✓	✓
	Liu [32]	Analyzed three typical location estimation schemes of triangulation, scene analysis and proximity.	✓	✓	✓	
	Seco [33]	Focused on mathematical methods used for indoor positioning systems based on RF signals, included geometry, minimization of the cost function, fingerprinting and Bayes.	✓	✓	✓	
Applications	Davidson [34]	Summarized indoor localization methods based on modern smartphones, integrated different types of measurement signals will improve localization performance.		✓	✓	
	Kuutti [35]	Evaluated and compared recent vehicle localization techniques and investigates their applicability on autonomous vehicles.	✓			
	Gu [36]	Gave a comprehensive survey of indoor positioning systems which were related to commercial products and research-oriented solutions from the viewpoint in a personal network.	✓	✓		

the parameters of the model training, but can also be utilized to determine the optimal datasets, optimal placement of signal sources, data compensation, dimensionality reduction, and other optimization problems. Owing to the privacy of cloud services and location tasks, the intention of this framework is to adopt the characteristics of chaos theory and encryption algorithms to solve the security problem.

The location strategy layer includes preprocessing and decision sublayers. If there is a lot of noise in the collected signals, the Kalman filter (KF) and particle filter are used for the preprocessing. And PCA is usually utilized for reducing dimension with less training time. A normalization algorithm is recommended to mitigate the problem of different equipment with different measurement accuracies, which is fast and effective. Chaos theory has a strong ability to address nonlinear problems, and it can be used for data preprocessing. The reconstructed data are transmitted to the decision sublayer, and the location algorithm is designed by ML and intelligent algorithms. A positioning problem is often accompanied by a trajectory tracking problem. The position at the next moment is directly related to the current position; hence, the joint Bayesian probability algorithm can further improve the positioning accuracy. The ultimate goal of the positioning problem is to provide the corresponding services, and then design a localization app for users.

IV. LOCALIZATION PRINCIPLES OF VARIOUS FINGERPRINTS

In this section, we initially take the localization system based on WiFi signals as an example, to elaborate the implementation principle of position fingerprint methods. Next, we divide the position fingerprints into five types (including RSSI, CSI, Bluetooth, magnetic field, and visible light) and explain their localization principles.

Indoor localization is increasingly required, including for fire protection, schools, shopping malls, hospitals, parking lots, rail trains, logistics warehousing, and underground operations. Especially in such fields as public safety, subways, and mine operations, the demand for indoor positioning technology is more urgent. For outdoor positioning technology, its application scenarios are mostly open environments, and localization errors as large as tens of meters will not affect the user experience. However, indoor positioning technology requires submeter localization accuracy to meet user

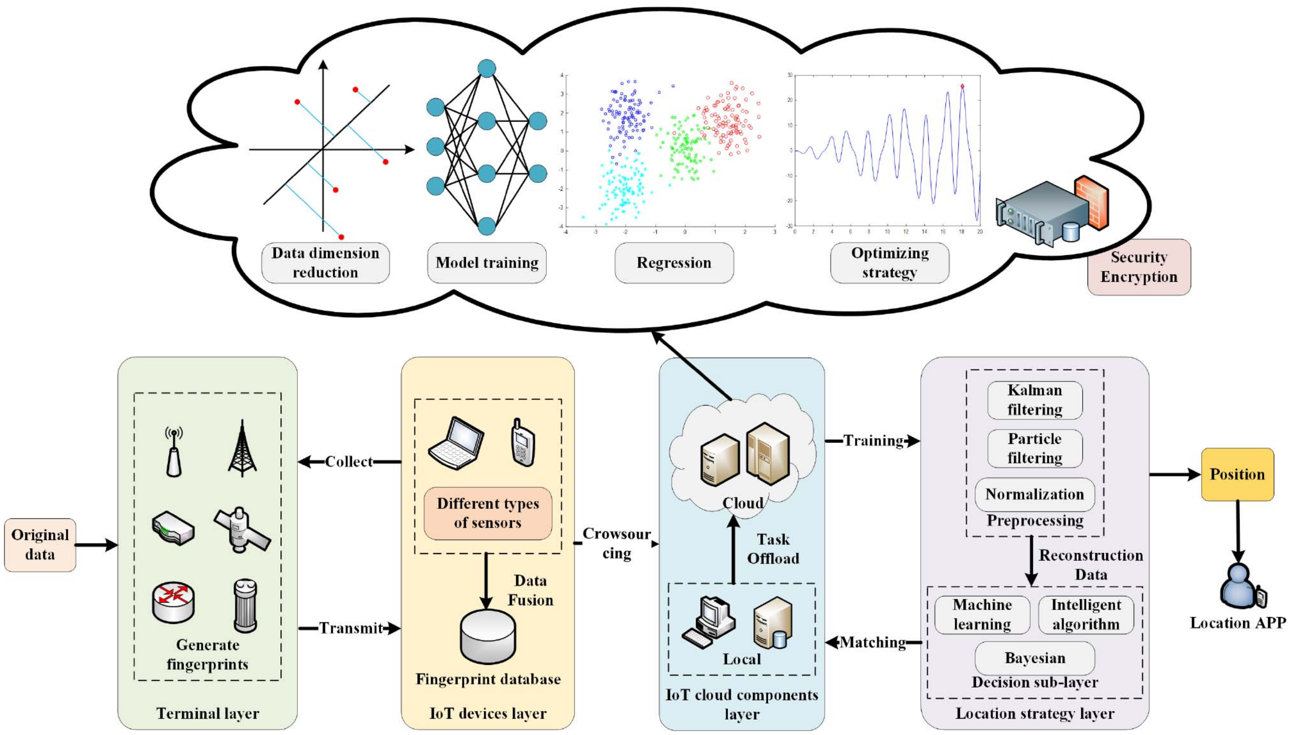

Fig. 1. Intelligent Localization architecture.

TABLE III
COMPARISON OF VARIOUS POSITIONING TECHNOLOGIES

Technology	Advantages	Disadvantages
WiFi	Easy to implement, expand, and measure; low cost	It takes a lot of work to build a fingerprint database. Even if the indoor environment changes only slightly, new fingerprints still need to be collected.
RFID	High accuracy, low cost	The deployment process is tedious and not suitable for most users' portable devices, and the communication distance is short.
IR	High accuracy	It needs special equipment, high cost, unable to penetrate obstacles, high power consumption, and easily affected by the environment.
UWB	High accuracy, low cost, strong penetration, fast transmission rate	It requires special equipment, high cost, and hardly popularized.
ZigBee	Physical and MAC layer, low cost, low power	Easily affected by the environment, poor system stability, not easy to achieve on most user equipment.
Ultrasonic	High accuracy, easy to implement	Easily affected by the multipath effect, need special equipment, high cost.

needs. To achieve high-precision positioning in indoor environments, researchers have proposed a number of positioning technologies and systems by combining wireless networks, sensor technology, signal processing, and many other cross-field technologies. Table III shows a comparison of various positioning technologies: WiFi, radio-frequency identification (RFID), infrared (IR), ultra-wideband (UWB), ZigBee, and ultrasonic. Although there have been many related studies on these localization systems, special sensors and other equipment are needed. Considering the cost, resources, deployment, and other problems, it is difficult to popularize and use these types of localization systems, except for WiFi. The fingerprint location method stands out for its unique advantages represented by WiFi. Although the process of constructing a fingerprint database is tedious, some studies have solved this problem successfully by adopting technologies such as collaborative localization.

Since the promulgation of the IEEE 802.11 protocol, wireless local area networks have been rapidly popularized throughout the world, and WiFi networks are the most widely used, which utilize radio frequency (RF) technology. WiFi has the characteristics of low cost, fast transmission rate, and convenient deployment. Especially for indoor environments such as airports, campuses, residences, office buildings, and hospitals, WiFi has become the principal means of network deployment. WiFi fingerprint positioning technology is a combination of signal acquisition and a positioning process, and has become an effective solution for indoor positioning technology, such as Horus [40] and RADAR [41]. The RSSI or CSI can be taken as the fingerprint of the WiFi signal, and a

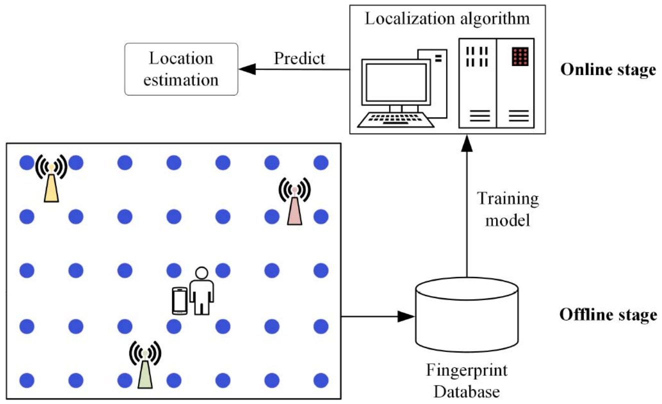

Fig. 2. Indoor localization based on WiFi fingerprint.

relevant localization algorithm is utilized to obtain the user's location information. The implementation process is shown in Fig. 2. There are two main stages: offline (training) and online (matching). For the offline stage, let us take the RSSI signal as an example. WiFi fingerprint signals from different APs are collected, and "multidimensional" fingerprint data for each location are saved to form an offline fingerprint database. In the online stage, the RSSI signal collected by the user is input to the localization system at a certain location. The localization algorithm finds the fingerprint data that best matches this signal, and estimates its position to realize the localization. It can be computed based on minimization of the Euclidean distance:

$$\hat{x} = \arg\min_{x_j} \left(\sum_{i=1}^{n} (r_i - \rho_i(x_j))^2 \right) \tag{1}$$

where r_i is the measured RSSI during the online stage, $\rho_i(x_j)$ is the offline fingerprint database.

A. Received Signal Strength Indicator (RSSI)

The RSSI is the most widely used fingerprint signal, owing to its convenient acquisition. The measurement unit is dBm, which reflects the strength of the measured signal in real time. Users match the collected multidimensional RSSI fingerprint signals with the fingerprint database, and use ML or a joint probability algorithm to calculate the estimated position of users, such as the maximum likelihood estimation method or naive Bayes method. Under ideal environmental conditions, the signal strength relationship between receiver and transmitter is as follows:

$$P_r(d) = P_t \frac{G_t G_r}{(4\pi d/\lambda)^2}, \tag{2}$$

where d is the distance between the receiver and the transmitter, $P_r(d)$ is the corresponding received signal strength, P_t is the signal transmitter power, G_t is the antenna gain of the transmitter, G_r is the antenna gain of the receiver, and λ is the signal wavelength. However, owing to the influence of complex indoor environmental factors, such as the temperature, humidity, signal interference, and obstacle shielding, the signal strength is less than that of the transmitted signal. The path loss model is often used to represent the signal strength of the receiver. The formula is as follows.

$$p(d) = p(d_0) - 10n\log_{10}\left(\frac{d}{d_0}\right) + G_\sigma, \tag{3}$$

where d_0 is the reference distance; $p(d_0)$ is the corresponding path loss value; n is the attenuation coefficient, which is dependent on the environment and has a value in the range 2–5; G_σ is a random variable with variance 2 that follows a normal distribution. It can be seen that the signal strength decreases with increasing propagation distance.

The location method based on the signal attenuation model has the characteristics of low requirements for equipment, simple operation, low cost, and no need for additional infrastructure, which has attracted much attention from researchers. However, the signal propagation model is overly idealistic. In actual environments, owing to the influences including personnel flow, signal occlusion, and spatial structures, the actual energy value of a propagating signal is different from the measured value at the receiver; hence, affecting positioning accuracy. Therefore, researchers took the intensity value of the wireless signal as a scene feature and proposed indoor location technology based on fingerprints combined with ML and intelligent algorithms. The localization problem is transformed into a feature matching problem, which mines the relation between position and signal strength by extracting multiple signal strengths from different locations as feature vectors. Because the "multidimensional" signal strength measured at different locations is unique, in analogy with a human fingerprint, this localization matching algorithm is called "fingerprint" localization. The core of a fingerprint-based localization algorithm is the matching algorithm. In theory, even if the collected signal strengths are affected by environmental factors, as long as the training samples are sufficient and the algorithm is reasonable, and the weights of the network are adjusted by using an ANN and other methods in the offline stage, then the positioning accuracy can be improved with better fault tolerance.

B. Channel State Information (CSI)

Localization systems based on the RSSI have unstable positioning performance owing to the influence of environmental factors, such as the multipath effect. In contrast with the RSSI, which only provides the average signal strength of the whole channel, the CSI of the physical layer is obtained by using an Intel 5300 network card that supports the IEEE802.11a/g/n standard; it as a fine-grained indicator to represent signal characteristics and has gradually been gaining attention.

In the orthogonal frequency division multiplexing (OFDM) technology, CSI signals utilize the information contained in different subcarriers in a single channel, and the subcarriers are orthogonal to each other, which has strong anti-interference effects and can effectively reduce the influence of the multipath effect. Therefore, it has attracted much attention from scholars. Many studies have used CSI signals as fingerprints for indoor positioning technology to improve the localization accuracy [42]–[46]. CSI describes the transmission process of a signal between a transmitter and receiver, and includes information such as signal attenuation, scattering, and delay distortion. Its expression is as follows:

$$\vec{R} = CSI \cdot \vec{T} + \vec{G}, \tag{4}$$

where $\vec{T}$ represents the signal vector at the transmitter, $\vec{R}$ represents the signal vector at the receiver, $\vec{G}$ represents the Gaussian noise vector, and *CSI* represents the channel matrix, the dimensions of which depend on the number of subcarriers. The channel frequency response CSI_i of each subcarrier i is a complex number, which can be expressed as:

$$CSI_i = |CSI_i| e^{j \angle CSI_i}, \tag{5}$$

where $|CSI_i|$ and $\angle CSI_i$ represent the amplitude and phase of *i*th subcarrier, respectively. When constructing the fingerprint database, the stability of signals and the obvious differences among fingerprints are necessary. If the fingerprints of two different locations are similar, the positioning accuracy will be affected. Because the CSI is a physical layer characteristic and can distinguish signals from multiple paths, it is more stable than the RSSI and suitable for high-precision positioning.

C. Other Types of Fingerprints

1) Bluetooth: With the emergence of the Bluetooth 4.0 standard, Bluetooth Low Energy (BLE) technology has also developed rapidly, which has the characteristics of stable signals, low power consumption, and high positioning accuracy. Localization systems based on Bluetooth have also become a current focus of active research [47]. Similar to the localization based on WiFi, Bluetooth collects the RSSI signal and combines ML and other algorithms for localization. Apple and Google have respectively proposed iBeacons and Eddstone Bluetooth devices, which have the characteristics of small size and low cost, enabling the large-scale indoor deployment of Bluetooth devices, and relevant studies have realized high-precision positioning. With the improvement and development of Bluetooth technology, the feasibility and reliability of Bluetooth-based indoor positioning technology have also improved.

2) Magnetic Field: Inspired by homing pigeons using magnetic fields for navigation, researchers have proposed magnetic field-based localization and navigation technology for high-altitude, ground, underwater, and other scenarios. However, as the magnetic field presents different distribution states under the influence of indoor complex environments, it can be regarded as a location fingerprint similar to the RSSI signal to achieve indoor positioning. The key is to establish the indoor magnetic field model, which affects the positioning accuracy. The point dipole model is given as follows

$$B(\vec{m}, \vec{r}) = \frac{\mu}{4 \times \pi} \left[3 \frac{(\vec{m}, \vec{r})\vec{r}}{|\vec{r}|^5} - \frac{\vec{m}}{|\vec{r}|^3} \right] \tag{6}$$

where μ is permeability of free space, $\vec{m}$ is the magnetic moment and $\vec{r}$ is the distance between the dipole and the observation point. This method does not depend on additional infrastructure, and can better reflect its advantages of easy implementation in indoor scenes without a network or light source. Generally, magnetic field-based indoor positioning technology is mostly implemented by filtering algorithms (such as the particle filter and KF algorithms), or combined with other positioning technology [48].

3) Visible Light: Visible light communication (VLC) is a technology that utilizes a light-emitting diode (LED) as the light source, based on the green communication concept, and poses a new challenge to traditional RF technology. It is regarded as a promising future IoT technology. This method only needs the light intensity collected by sensors for positioning, and no other hardware equipment is needed. The received signal after optical to electrical conversion is

$$r(t) = \alpha R_p x(t - \tau) + n(t) \tag{7}$$

where α is the attenuation of the LED, τ is the flight time, R_p is the responsivity of the photodiode and $n(t)$ is the shot noise [49]. With simple operation, low cost, and freedom from the influence of the multipath effect, it can also achieve high precision. Compared with traditional indoor positioning technologies, it has obvious advantages and has been paid much attention by scholars.

In Table IV, the advantages and disadvantages of the abovementioned wireless fingerprint types are compared. In addition, IR, RFID, UWB, ultrasound, and other types of signals are utilized for indoor positioning systems. Because this study is mainly focused on an overview of localization technology using ML and intelligent algorithms, other types of signals or technologies (such as AoA, ToF, and TDoA) are not within the scope of this work, and interested readers are referred to other surveys [1], [50], [51].

V. INTELLIGENT LOCALIZATION TECHNOLOGY

This section outlines the application of ML and intelligent algorithms in indoor positioning systems and technologies based on various fingerprint signals. The location accuracy, energy consumption, complexity, and other aspects of different localization systems are compared in detail.

A. RSSI-Based ML

1) K-Nearest Neighbor: The KNN algorithm is the most widely used ML algorithm in indoor positioning systems. The key idea is to match the collected RSSI signals with the fingerprint database, find the closest K fingerprints, and take the coordinate average value as the estimated position. Computation of the signal distance to each fingerprint by utilizing

$$d = \sqrt{\sum_{l=1}^{L} \left(RSSI_{m,l} - RSSI_l\right)^2} \tag{8}$$

Bahl *et al.* [41] proposed RADAR, which analyzed the space propagation model of wireless signals, and applied the KNN algorithm to indoor positioning for the first time. They considered that the average value of K neighbor coordinates is closer to the real location than a single neighbor. The experimental environment is a floor of 980 square meters with more than 50 office rooms, and its average localization error is

TABLE IV
ADVANTAGES AND DISADVANTAGES OF DIFFERENT FINGERPRINTS

Fingerprint	**Advantages**	**Disadvantages**
RSSI	WiFi is everywhere, easy to deploy, low-cost, the most widely used location fingerprint signal.	It is susceptible to the multipath effect, coarse-grained, the noise interferes with the training model and affects the positioning accuracy.
CSI	Compared with the RSSI, the signal is more stable, not affected by the multipath effect, fine particle size, and high precision.	Multichannel leads to random signal phase, hardware acquisition equipment and driver need to be modified.
Bluetooth	Smartphones can be used to collect signals, without expensive equipment, low power consumption.	Relying on the RSSI signal limits positioning accuracy, and the costs of calibration signal and training the model are high.
Visible light	Indoor environments have widely deployed LEDs; light is easy to collect and the system is expandable.	Acquisition of signals is interfered with by natural light, line of sight is required.
Magnetic field	Unique natural environment signal, it is not affected by the multipath effect.	Interference of magnetic field signal by indoor environmental structure requires extra calculation cost of the calibration signal.

2–3 m. This is the first attempt to apply a ML method to wireless indoor positioning, which has laid a solid foundation for later research. By studying the correlation between the K value and RSSI, Oh and Kim [52] proposed an algorithm to adjust the K value for different positions. Compared with the traditional KNN algorithm with a fixed K value, the accuracy increases by 30% and the median error is approximately 1 m. Xie *et al.* [53] proposed replacing the Euclidean distance in the KNN algorithm with the Spearman distance. The simulation results show that the improved method is superior to the original KNN method and suitable for indoor environments with multipath signal attenuation and time dynamics.

Hossain *et al.* [54] found that even under the same wireless conditions, there were significant differences in the RSSI between different hardware devices. The definition of signal strength difference for fingerprint was proposed, and its performance was experimentally verified by the KNN algorithm using a variety of different mobile devices and heterogeneous hardware. Li *et al.* [55] considered that existing technologies do not take into account the fact that the same RSS differences at different RSSI levels do not imply the same geometric distance differences in complex indoor environments. According to the effective signal distance between the signal vector and the reference fingerprint in the radio map, a scaling weight based on the RSSI level was introduced. Therefore, a KNN algorithm based on feature scaling was proposed to improve the accuracy, and a localization error of 1.70 m was achieved. Xue *et al.* [56] improved the selection of the neighbor reference points in the KNN. The physical distance between neighbor reference points and test points was utilized to avoid the problem of inaccurate positioning caused by selecting reference points only located on one side of the test points.

2) Extreme Learning Machine (ELM): The ELM has the characteristics of a close network structure and rapid learning, which can effectively solve the problems of excessive training time of an offline fingerprint database [57]–[59]. ELM with L hidden nodes can be represented by

$$\sum_{i=1}^{L} \beta_i g\big(W_i \cdot X_j + b_i\big) = o_j, j = 1, \ldots, N \tag{9}$$

where $g(\cdot)$ is the activation function, β_i is the weight vector. If T is the corresponding label of X and $H = g(W_i \cdot X_j + b_i)$, the goal of ELM is a minimizing loss function as

$$\beta = \arg\min_{\beta} \|H\beta - T\| \rightarrow \beta = (H^T H)^{-1} HT. \tag{10}$$

Khatab *et al.* [60] proposed ADELM to improve the positioning performance of feature extraction and classification by using deep learning, extreme value learning, and a self-encoder instead of random weight generation. At the same time, the influence of increasing the training data on the accuracy was shown in the experimental results. Zou *et al.* [61] transformed the RSSI into the standardized location fingerprint based on Procrustes analysis, and introduced a similarity metric named the signal tendency index (STI) for matching. They combined the advantages of the STI and a weighted ELM to design a localization algorithm. It was also proved that the proposed positioning system has good robustness against device heterogeneity. Zou *et al.* [62] utilized an online sequential ELM to solve two problems, which are that model training is time-consuming and laborious in the offline stage, and the method is inflexible for environmental changes. Comparative experiments showed that this method has higher positioning accuracy and fast online sequential learning speed under various environmental changes (such as opening and closing doors and variations of occupancy distribution), and its performance is better than the existing methods.

3) Support Vector Machine (SVM): The SVM is a ML method based on statistical theory, which has certain advantages in processing high-dimensional data and nonlinear problems, especially in dealing with the regression problem between fingerprints and positions. It is given as follows

$$\begin{aligned} &\arg\min_{W,b} \ \frac{1}{2}\| W\|^2 + C\sum_{i=1}^{n} \xi_i^p \\ &\text{sugject to } \ y_i(W(\psi(x_i)) + b) \geq 1 - \xi_i, i = 1, \ldots, n \end{aligned} \quad (11)$$

where $W(\psi(x_i)) + b$ is the decision boundary; y_i is the corresponding label of x_i; C is the error penalty coefficient and ξ is the approximation of the number of misclassified samples.

Wu *et al.* [63] proposed an indoor localization algorithm based on an online independent SVM and undersampling technology. The selection of the kernel function parameters was designed in the training process, which significantly reduced the time complexity, and a median accuracy as high as 1.2 m was achieved. This could be a solution for portable devices with limited processing capacity and memory. Figuera *et al.* [69] suggested that prior information should be considered to improve the localization performance before training the model of fingerprint databases, and three localization algorithms with prior information were proposed based on SVM. The third SVM-CC algorithm utilized autocorrelation kernels and complex outputs to provide the best performance in terms of all the test quality indicators.

4) Artificial Neural Network (ANN): As the most representative algorithm in ML, the ANN has been rapidly developed in recent years. Because its mutilayer network structure can fit different complex changes of a nonlinear model, it is also suitable for localization problems. As long as the training model works well, it can locate accurately, and can resist the influences of noise and the multipath effect. Take DBN as an example, (x^k, y^k) represents the sample of the fingerprint database, the updated parameters with gradient descent algorithm which can be described as follows:

$$\left(\hat{W}, \hat{b}\right) = (W, b) + \alpha\frac{\alpha}{\partial(W, b)}\sum_{k=1}^{m} J(W, b; x, y) \quad (12)$$

where $J(\cdot)$ is utilized to predict position, α is the learning rate and m is the batch size.

Meng *et al.* [70] utilized the weighted-median Gaussian filtering algorithm to preprocess the RSSI to establish a fingerprint database and reduce the training time. An improved fast clustering algorithm was proposed to design the network structure, and it was combined with the Levenberg–Marquardt algorithm for localization. The minimum median accuracy of 1.459 m was achieved. Félix *et al.* [71] studied the influence of the pretraining algorithm for the localization system, and utilized deeper machines to improve the accuracy and reduce errors in dynamic indoor environments. DNN, DBN, and GB-DBN were used to train the model. The average localization error was less than 2 m, and the best result of 1.00598 m was achieved by using DNN.

According to the correlation between the initial parameters of the NN and the mean square error (MSE), Mok and Cheung [64] proposed an algorithm by modeling a complex WiFi signal propagation surface. They suggested retrying different initial parameters and different input orders of the AP data to train the model to find the optimum parameters, so as to improve the localization accuracy. Dinh-Van *et al.* [65] considered whether the environment constraints improve localization results for indoor intelligent vehicle, and utilized a raw data smoothing technique with an ensemble classification ANN to deal with noisy RSSI. The experiments showed a 2.25 m of average localization error.

5) Bayesian: The Bayesian classifier estimates probabilities for localization by a statistical method. The data in the fingerprint database are classified according to sampling points, and the location information is determined by the real-time RSSI. The probability distribution of RSSI is $p(\mathrm{x}|r_1, \ldots, r_n)$, location problem maximises the posterior probability which can be represented by

$$\hat{\mathrm{x}} = \arg\max_{\mathrm{x}}(p(\mathrm{x}|r_1, \ldots, r_n)). \quad (13)$$

And it is computed by Bayes' theorem to get the distribution of the location

$$p(\mathrm{x}|r_1, \ldots, r_n) = \frac{p(r_1, \ldots, r_n|\mathrm{x})p(\mathrm{x})}{p(r_1, \ldots, r_n)} \quad (14)$$

The priori information is uniform with equal probability in the most existing researches [72], it is regarded as a normalizing constant which the problem becomes to compute the Maximum Likehood estimation

$$\hat{\mathrm{x}} = \arg\max_{\mathrm{x}}(p(r_1, \ldots, r_n|\mathrm{x})). \quad (15)$$

Madigan *et al.* [73] proposed a Bayesian hierarchical model by utilizing prior information, which eliminated the need for training data compared with existing methods. The concept of a completely adaptive zero-analysis method was introduced to estimate the position. Atia *et al.* [66] introduced an improved Bayesian regression algorithm to estimate the probability distribution of the posterior signal strength at all positions according to the online observation of APs, which could be used to dynamically estimate and calibrate the radio map. In order to adapt continually to the dynamic changes, the Bayesian kernel parameters were constantly updated and optimized based on the latest APs observations. Two different experiments were performed on an IEEE 802.11 network, and the median accuracy of was 2–3 m was achieved. Oguntala *et al.* [74] used the multivariate Gaussian to design a novel ambient human activity recognition framework based on RFID. It suits well for the single and multi-dwelling environment.

6) Random Forest: Random forest (RF) is an integrated classifier composed of a group of decision trees, which is similar to the Bayesian method. D_t represents the samples used by h_t and $H^{oob}(x)$ is the out-of-bag estimate error of x,

$$H^{oob}(x) = \arg\max_{y\in Y}\sum_{t=1}^{T} I(h_t(x) = y)\cdot I(x \notin D_t) \quad (16)$$

then, the generalization error is

$$\varepsilon^{oob} = \frac{1}{|D|}\sum_{(x,y)\in D} I\Big(H^{oob}(x) \neq y\Big). \quad (17)$$

Guo *et al.* [67] constructed a set of fingerprint databases based on different types of wireless signals, and proposed an

TABLE V
DIFFERENT MACHINE LEARNING ALGORITHMS BASED ON RSSI

Solutions	Accuracy	Latency	Complexity	Robustness	Coverage	Characteristics
Bahl [41]	2–3 m	Low	Medium	Medium	Broad	It is easy to implement and uses KNN for localization with low accuracy.
Oh [53]	1 m	N/A	Low	Strong	Narrow	The correlation between K value and RSSI is used to adjust K value adaptively.
Xue [57]	3–4 m	Low	Low	Weak	Narrow	The selection method of the nearest neighbor nodes is improved in KNN.
Khatab [61]	N/A	N/A	High	Strong	Broad	It has better training model and test speed by utilizing automatic coding machine and ELM.
Zou [63]	1–3 m	Low	High	Strong	Broad	The system is flexible in response to environmental changes, especially considering the effects of opening and closing doors on the experimental results.
Wu [64]	1.2 m	Low	Medium	Strong	Broad	Reduced computational complexity, suitable for portable devices with limited processing power and memory.
Mok [65]	4 m	N/A	High	N/A	Broad	The nonlinear WiFi signal propagation surface is modeled and trained by NN.
Dinh-Van [66]	2.25 m	Low	High	Strong	Broad	The ensemble classification method and environment constraints are utilized to solve the multipath effect and low scanning frequency.
Atia [67]	2–3 m	N/A	Medium	Strong	Broad	Bayesian kernel parameters are constantly updated to dynamically estimate and calibrate radio maps.
Guo [68]	N/A	Low	High	Medium	Narrow	RF is used to construct different classifiers, and sliding window is set to ensure the robustness against environment changes and noise.
Guo [69]	N/A	Low	High	Medium	Narrow	Considering the five types of fingerprints including RSSI, AdaBoost is used to construct different classifiers.

efficient fusion algorithm to improve the localization accuracy. The idea of RF is used to construct different classifiers with multiple samples in the fingerprint database, and sliding windows are set to ensure the robustness to environmental changes and noise. Górak and Luckner [75] proposed an improved RF to compose the location model for each AP, and the change in location performance when certain APs failed was especially considered. Mo *et al.* [76] proposed a rough location method based on RF. This method could customize multiple subregions and classify test points. Compared with typical clustering algorithms, it had higher accuracy. The kernel principal component analysis (KPCA) algorithm was applied to wireless map processing. The feasibility and reliability of the algorithm were verified by a theoretical analysis and experiments.

7) AdaBoost: The concept of AdaBoost is to combine several weak classifiers to obtain a high-precision classifier, which is simple, fast, and improves the unstable classification algorithm. According to the additive model, it can be represented as

$$H(x) = \mathrm{sign}\left(\sum_{t=1}^{T} \alpha_t h_t(x)\right) \tag{18}$$

which is utilized to minimize the exponential loss function $\ell_{\exp}(H|D) = E_{x\sim D}[e^{-f(x)H(x)}]$.

Guo and Ansari [68] proposed the GOOF, which merges five types of fingerprints into a database, and designed a parallel multiclassifier based on AdaBoost. Each fingerprint was trained as five strong multiclassifiers in parallel, and a multiple-classifiers-multiple-samples algorithm was proposed to improve the positioning accuracy by combining the multiclassifier predictions of different samples. Feng *et al.* [77] pointed out that the accuracy of AdaBoost depends on all the weak learning classifiers, and if there is noise in the fingerprint, the performance of AdaBoost will deteriorate. Therefore, an improved AdaBoost algorithm was proposed to improve the accuracy, which ignores the single unfocused point. Bozkurt *et al.* [30] pointed out that utilizing AdaBoost integration algorithm can improve the performance of decision tree classifiers. The effect is essentially the same as that of the KNN, and it can be seen as the best classifier for indoor location.

The performances of the various ML methods discussed above, which are widely utilized based on RSSI signals, are compared in detail in Table V, including their positioning accuracy, delay, computational complexity, robustness, coverage, and characteristics. In addition, there are many other ML methods that can also be applied to indoor positioning, such as sequential minimal optimization, bagging, and semi-supervised learning [78], [79], which are not described in this paper.

To summarize, there are abundant works which have shown large improvement based on ML in localization accuracy. However, the computational complexity is still high due to the complex learn framework of ML, such as LSTM. And it is difficult to achieve cm-level precision due to the character of WiFi. How to reduce training time with high accuracy is the main challenge. Therefore, to address the time consuming issue, intelligent localization in the future work requires a high speed learn mechanism like Bayesian [73]. Moreover, sensing measurements are affected by multipath propagation and nLoS conditions, and intelligent localization technologies consider to select the reliable positional information based on the features extracted from samples. We can fuse other signals for improving performance [68] or involve hybrid models to reveal the relationships among different features.

Environmental knowledge is also essential to exploit intelligent localization based on unsupervised ML such as contextual data which includes electronic maps and agent profiles. For the harsh wireless propagation scenarios, we consider the nLoS detector with $\delta \in \{0, 1\}$ where 0 and 1 correspond to LoS and nLoS conditions, respectively. Then environmental parameters can be calculated by means of posterior probabilities of error

$$\begin{cases} \varepsilon_{nLoS} \triangleq P\{nLoS|\delta = 0\} = \frac{p_{nLoS}}{P_0} P\{\delta = 0|nLoS\} \\ \varepsilon_{LoS} \triangleq P\{LoS|\delta = 1\} = \frac{1-p_{nLoS}}{1-P_0} P\{\delta = 1|LoS\} \end{cases} \tag{19}$$

where $p_{nLoS} = P\{nLoS\} = 1 - P\{LoS\}$ is the probability of nLoS condition and $P_0 = P\{\delta = 0\} = 1 - P\{\delta = 1\}$. And intelligent localization can refine the measurements based on environmental information or discard the unreliable measurements for providing agent positional information.

B. CSI-Based ML

Wu *et al.* [92] utilized a CSI signal to establish a transmission model and designed a localization algorithm based on the frequency diversity of subcarriers in the OFDM system. They proposed the a FILA system and implemented it on 802.11 network interface cards (NICs). The experimental results showed that the accuracy could be significantly improved compared with the corresponding RSSI methods. It can be seen as one of the origins of the application of the CSI to localization technology. This paper is highly significant and provided a new research direction in recent years. Yang *et al.* [93] gave a detailed overview of the working principle of CSI signals in indoor localization, which was published in the same year, and made a careful comparison with the RSSI. This section summarizes and compares the existing indoor localization systems based on the CSI using ML algorithms.

1) KNN and SVM: Song *et al.* [80] proposed a localization system based on the CSI that calculates the Euclidean distance and time reversal resonance intensity between the target and reference points by using a multidimensional scale analysis method, and combined it with the KNN for location. The median accuracy as high as 1.203 m was achieved. Zhou *et al.* [81] utilized a density-based spatial clustering algorithm to reduce the noise in the CSI, and extracted the features with the greatest contribution for reducing the dimension of the CSI by PCA. They established the nonlinear relationship between the CSI and position by using the SVM. The positioning experiments were carried out under two typical scenarios, and the accuracies 1.22 and 1.39 m, respectively, were achieved. Li *et al.* [94] proposed a ML-based nLoS identification SVM and related channel information regression model method to solve the problem of nLoS recognition in positioning, which were used to identify the nLoS and reduce errors, respectively.

2) RF and Bayesian: Wang *et al.* [82] took the RF training model as a fingerprint in the offline stage to design the RFFP localization algorithm based on the CSI, which can save space and have better performance against the multipath effect. Compared with the KNN and WKNN, the RFFP has higher classification accuracy and lower average positioning error. Wu *et al.* [95] designed a passive indoor localization system based on the CSI, which utilized a naive Bayesian classifier according to the confidences. The experimental results show that the accurate rate of the localization was 86%, and the performance was improved by at least 15% compared with the baseline naive Bayesian classifier. Shi *et al.* [83] verified the unpredictability of the CSI measurement through experiments, and proposed a technology based on a probability fingerprint as the solution. PCA was used to filter the most relevant feature vectors and improve the localization efficiency. In addition, the motion trajectory of a moving object was tracked continuously by Bayesian filtering.

3) Deep Learning: Wang *et al.* [84], [96] proposed the PhaseFi, which is a indoor localization fingerprint identification system based on calibrated CSI phase information. In the offline stage, a deep network consisting of three hidden layers was designed to train the calibrated phase data and used weight to represent the fingerprint. A greedy learning algorithm was adopted to train the weights layer by layer to reduce the computational complexity, where the subnetwork between two successive layers constitutes a restricted Boltzmann machine (RBM). In the online phase, a probability method based on radial basis functions (RBFs) was utilized to estimate the position, and the experimental results showed that the localization performance was better than that of methods based on the RSSI. Wang *et al.* [72] proposed the DeepFi localization system with the same idea as system in [96], which utilized a back propagation (BP) neural network to reduce the error of training the model and improve the localization accuracy. Compared with the three existing algorithms, the DeepFi has obvious advantages and the best accuracy of 0.95 m was achieved under two representative indoor environments. The innovative CiFi system [97] was proposed which combined a deep convolutional neural network with the AoA method, and the generated AoA images were utilized to train the model. Then system could predict the location of mobile devices using the trained DCNN model and CSI-AoA images.

To summarize, CSI has fine-grained information to WiFi indoor localization as a physical signal. It has temporal and spatial characters which discriminate the locations and significantly improve the accuracy. However, it is necessary to modify the driver and OS core with a special NIC [96]. They may not be widespread to apply in a spacious area like terminal building [72], it is different from RSSI which can be collected directly by a smartphone. Therefore, a researcher may need to jointly consider the characters of CSI, and utilize the spatiotemporal changes of CSI signal for localization. Moreover, a clever method to collect data may be needed for minimizing manpower and resources. For example, intelligent localization can plan paths that maximize the utility of data collection for the robots based on reinforcement learning, and it is regarded as the informative path planning problem [16]. The mutual information can measure the informativeness as a criteria if we use the Gaussian process to model the distribution of fingerprint data in a target area. Thus, we also need to balance between cost in offline stage and improvement in online stage.

In addition, intelligent localization also encourages to utilize the direct positioning techniques to estimate the position based on the measurement model such as Eq. (4). The maximum likelihood and least squares can estimate the position, and direct positioning techniques can also improve the accuracy because there are more rich information in sensing measurements. And direct positioning techniques can result in efficient implementations according to the distributed Gaussian noise for each measurement.

C. Bluetooth-Based ML

Jiang *et al.* [47] utilized the fusion semi-supervised ELM and BLE to fuse multiple signals into a unified model. It was not like other semi-supervised methods that just separately consider multiple signals. Compared with some localization systems that use supervised or semi-supervised methods, it has obvious advantages of reducing the workload of manual calibration, improving the accuracy, and rapidly training and matching owing to the framework of semi-supervised learning. Takayama *et al.* [85] designed a composite fingerprint that consisted of the Bluetooth signal strength of multiple point-in-time according to location fingerprint and track estimation. They established a regression model to discuss the localization accuracy with the SVM and RF. The MSEs of 2.35 and 0.80 m were achieved. Xiaodong *et al.* [86] utilized the Building Information Model (BIM) and BLE technologies to solve the indoor map data collection for intelligent mobile terminals. Especially, they completed a visualization platform to display the location results based on BIM and the accuracy was about 1.5 m.

Similarly, the KNN algorithm is also widely utilized for Bluetooth. For example, Kanaris *et al.* [98] proposed the i-KNN algorithm for localization by combining a mixed method of BLE and 802.11 infrastructure. The initial fingerprint data can be filtered after considering the proximity of the RSSI to the BLE device. The i-KNN utilized a fragment of the initial dataset to achieve rapid location and improved the accuracy by minimizing computing errors. Peng *et al.* [99] utilized BLE and iterative weighted KNN (IW-KNN) to extend the service life of positioning equipment. IW-KNN selects a different iBeacon to obtain the RSSI in each iteration, and calculates the average position as the final result after several iterations. Compared with some improved KNN algorithms, the accuracy is reduced by 1.5–2.7 m. In addition, many studies have used Bluetooth with smartphones to design localization systems [100]–[102].

To summarize, BLE has higher energy efficiency, coverage range and often uses for collaborative localization. It relies on RSSI based inputs with less complex, combines with KNN and other ML methods which makes existing BLE based localization systems have less cost in offline stage. However, the reliance limits its accuracy and BLE beacons are not ubiquitous as WiFi. How to create and maintenance radio map is still the main problem, may be crowdsourcing is a better method. And BLE can provide potential submeter-level precision in proximity mode. Therefore, The BLE based positioning can be improved if we aid by other techniques such as map-matching and sensor measurements. Intelligent localization requires features extracted from the sensing measurements to provide useful information to determine whether a measurement represents the agent position. Since BLE is closely related to RSSI, we need to mitigate the errors of feature estimates based on Eq. (19). The bias β is the value of the feature due to harsh propagation, the estimation of single values $\hat{\theta}$ for a measurement α can be calculated by

$$\hat{\theta} = \begin{cases} (1-\varepsilon_{nLoS})\alpha + \varepsilon_{nLoS}(\alpha-\beta), & \text{if } \delta = 0 \\ \varepsilon_{LoS}\alpha + (1-\varepsilon_{nLoS})(\alpha-\beta), & \text{if } \delta = 1. \end{cases} \quad (20)$$

Considering the mobility of users and the convenience of using BLE on smartphones, intelligent localization can complete the adaptive updating of fingerprint maps by mobile swarm intelligence techniques. The relation model between adjacent fingerprints is established by transfer learning or manifold alignment based on the real-time fingerprint data, and then update the whole fingerprint map. It can dynamically adapt to environmental changes that may occur in long run processes.

D. Magnetic Field-Based ML

Shao *et al.* [87] designed a new hybrid positioning image based on WiFi and a magnetic fingerprint, and used a CNN to classify the position of the fingerprint images. Appropriate learning strategies were adopted for different network branches to prevent the CNN from overfitting. It was proved that this method could automatically learn the location mode, thus significantly reducing the workload in the offline phase and the positioning accuracy was approximately 1 m. Keser *et al.* [103] proposed the F-score-weighted indoor positioning algorithm, which combined the RSSI and a magnetic fingerprint by considering the differences in different types of signals. This method carried out maximum likelihood estimation on the WiFi-RSS signal values and magnetic signal value, and calculated the f-score of each signal as the weight for localization. The experimental results showed that this algorithm had better localization performance than the single signal. Subbu *et al.* [88] theoretically analyzed the reason for the uniqueness of the characteristic magnetic field in an indoor environments, and proposed a location method based on the signature of the characteristic classification for the magnetic field collected by smartphones, with a location error of approximately 2–6 m.

Shu *et al.* [104] proposed the Magicol for an indoor positioning and tracking system, containing local disturbances of the geomagnetic field. A two-channel bidirectional particle filter algorithm was designed to improve the accuracy by discussing the fusion of the magnetic signal and WiFi signal in depth. Furthermore, a compliance walk method for constructing the fingerprint database was proposed, which greatly reduced the workload in the offline stage. Experiments were carried out under typical indoor environments, with the best accuracy as high as 1 m. Analogously, Zhang *et al.* [89] proposed the DeepPositioning for combining RSSI and magnetic signal to obtain rich fingerprinting and deep learning is applied to extract rich intrinsic features. Xie *et al.* [105] proposed a reliability-enhanced particle filter for an indoor positioning system of smartphones based on the fact that most existing particle filter methods are affected by many factors and are not practical in real life. The dynamic step estimation algorithm and heuristic particle resampling algorithm were used to reduce the calculation cost and error. In large buildings, the average accuracy was 1–2 m.

To summarize, the magnetic field is everywhere as a characteristic of the Earth and only provides local localization due to its spatial ambiguity. We can conveniently use magnetometers or smartphones to establish the fingerprint database [88]. However, there are may be similar fingerprint features even the two sample points are far apart due to building materials interfere with the magnetic field. Making an efficient magnetic field map is still a open problem. Therefore, the fingerprints need to be preprocessed to magnify their feature differences for improving accuracy. May be it is important to create 3D magnetic field map and use a statistical model for future studies [104]. Combining with the characteristics of magnetic field, intelligent localization is considered to utilize the multidimensional scaling algorithm to transform the physical position into a high-dimensional fingerprint space, which breaks the fingerprint independence as one of the basic hypotheses of traditional fingerprint-based localization algorithms. And the "Dropout" technology can prevent the overfitting problem of training the high-dimensional data, which outperforms other regularization methods [28].

E. Visible Light-Based ML

Guo *et al.* [90] proposed a positioning algorithm that fused multiple classifiers based on visible light. Diodes placed at different grid points captured the various intensity-modulated sinusoidal signals that were emitted by LEDs, and two multiple classifiers were obtained by training the processed fingerprints with ML algorithms. Two robust fusion localization algorithms were proposed to combine the outputs of these classifiers. Guo *et al.* [106] proposed a VLC indoor location method based on a two-layer fusion network, and four types of LEDs with different powers were deployed to generate light intensity fingerprints in an environment of dimensions 3 m × 2 m × 1.48 m. In the diverse layer, it utilized a combination of multiple fingerprints and classifiers to predict the position, and an optimal weight search algorithm was proposed to intelligently determine the optimal parameters of the fusion positioning in the fusion layer. Saadi *et al.* [107] combined clustering and linear regression for application to the RSSI database composed of LED intensity variation. The difference between the data and the clustering center was reduced by using the trained clustering. A regression model was utilized to process the clustered data for partitioning data and thinning the results. In an indoor environment of dimensions 5 m × 5 m × 4 m, the positioning accuracy reached 40 cm.

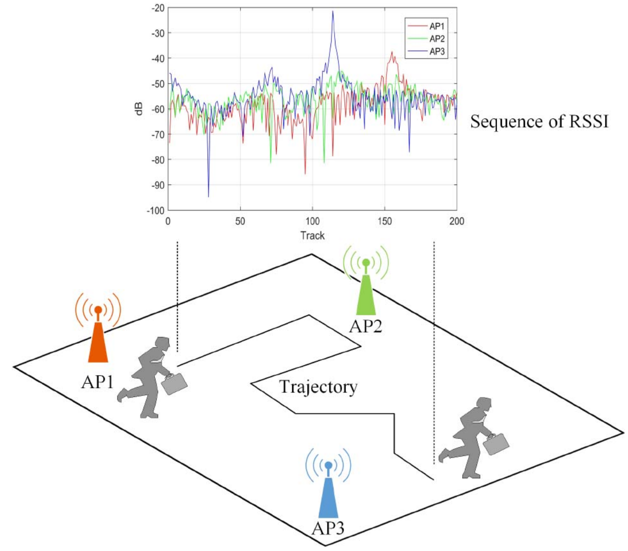

Fig. 3. Time series of fingerprints.

Zhao *et al.* [91] took common smartphones as receivers and light intensity values as location signatures, and proposed the NaviLight as a universal navigation framework for indoor positioning that can also provided real-time services on Android phones. Because the light strength is variable and a single light does not have enough discrimination, the LightPrint was proposed, which can rapidly match the light fingerprint by constituting vectors of multiple light strength values. The change in light fingerprints was considered as a time series, which were dealt with by utilizing the classical dynamic time warping (DTW) algorithm. Experiments were carried out in three indoor environments with a total area of over 1000 square meters, including an office, mall, and underground parking, and submeter positioning accuracy was achieved. Similarly, the temporal and spatial changes in the signal were regarded as time series for positioning in the trajectory tracking system as shown in Fig. 3. The DTW algorithm is used to design the feature matching algorithm. Gradim *et al.* [108] utilized linear regression supervised learning to optimize the parameters of the density-based spatial clustering of applications with noise (DBSCAN) by a set of training samples for which the actual positions were known. The simulation results showed that the accuracy of the system was improved by 35%, with a moderate increase in complexity. Table VI compares the above methods and highlights their respective advantages.

To summarize, visible light widely covers a scale even more than WiFi which can be used for indoor localization.

TABLE VI
COMPARISONS OF EXISTING INDOOR LOCATION SYSTEMS

Solutions	**Fingerprint**	**Method**	**Accuracy**	**Characteristics**
Song [81]	CSI	KNN	1.203 m	The Euclidean distance between the target point and the reference point is calculated by MDS.
Zhou [82]	CSI	SVM	1.22 m	DBSCAN is used to reduce the noise in CSI, and PCA is used to reduce the dimension of CSI.
Wang [83]	CSI	RF	<1 m	It can save storage space and against the multipath effect.
Shi [84]	CSI	Bayesian	N/A	The fine-grained subchannels measure the physical parameters and improve localization and tracking accuracy.
Wang [85]	CSI	DL	1–2 m	Combines RBM with probability method to locate.
Jiang [47]	Bluetooth	Semi-supervised learning	N/A	Reduce manual calibration, integrate multiple signals into a unified model, and rapid training and testing.
Takayama [86]	Bluetooth	SVM, RF	0.8–2.35 m	The fusion of position fingerprint and dead reckoning to form the composite fingerprints, which can improve accuracy.
Gong [87]	Bluetooth	BIM	1.5 m	An intelligent mobile terminal indoor positioning platform is developed to realize the 3D positioning of the intelligent mobile terminal.
Shao [88]	Magnetic	CNN	1 m	The RSSI and magnetic field fingerprint are fused into a mixed position image, and the position of the fingerprint image is classified by CNN.
Subbu [89]	Magnetic	DTW	2–6 m	It provides real-time location services based on smartphones and is easy to expand.
Zhang [90]	Magnetic	DL	1.45–1.94 m	The intelligent fusion of RSSI and magnetic signal can effectively improve smartphone indoor localization.
Guo [91]	Visible light	ML	<5 cm	The localization performance is further improved by constructing multiple classifiers and providing two fusion algorithms.
Zhao [92]	Visible light	DTW	<1 m	It proposes a universal indoor positioning and navigation framework, in which the user can collect light intensity fingerprints while walking, which minimizes user efforts.

AoA technique as the main method for visible light which is difficult to implement, and ML gradually replaces AoA to achieve high precision localization. However, there are still two limitations, one is that LoS between LEDs and sensors is necessary; another is that the changes of light strength, especially interference from the sun. Both will affect the positioning accuracy, may be it is a better way to consider the changes as time series [91]. Intelligent localization can utilize the Dickey-Fuller Test for checking stationarity, and the Auto Regressive model is utilized to predict and analyze the time series. In addition, we can also use the Hidden Markov Model which can migrate measurements from one state to another state to dynamically update the fingerprint map.

F. Indoor Localization Based Intelligent Algorithms

Intelligent algorithms are often utilized to solve optimization problems in engineering and other fields, such as the simulated annealing algorithm (SAA), genetic algorithm (GA), and differential evolution algorithm (DEA). Similarly, certain problems in the positioning process are transformed into optimization problems to design and implement the positioning algorithms [120], [121]. This section introduces the existing applications of intelligent algorithms for localization based on different types of fingerprints.

Owing to the complexity of indoor wireless communication environments, determining how to optimize the location of APs to improve positioning accuracy is still a challenging and difficult problem. Zhao *et al.* [109] discussed an indoor wireless transmission model and proposed a new AP location optimization model, in which all sampling points should be maximized to increase the difference and diversity array of signal strength, so as to improve the accuracy of location fingerprint positioning. On this basis, a DEA for optimization problems was proposed. As described in the previous section, the KF is usually use to solve the problem that signals are susceptible to the multipath effect [122], which leads to training samples with certain errors when constructing the fingerprint database. Some scholars also proposed the use of a GA to design a nonlinear filter as a new optimization method for indoor navigation technology [110].

Wang *et al.* [111] combined the Particle Swarm Optimization (PSO) algorithm with a BP neural network and proposed the pso-bp algorithm to determine the relationship between the signal and the tag position of the positioning system. It utilize a group of random particles to find the optimal result. If *pbest* represents the personal best and *gbest* represents the global best, we can have

$$v_{k+1} = w \cdot v_k + r_1 c_1 \cdot (pbest_k - p_k) + r_2 c_2 \cdot (gbest_k - p_k),$$
$$p_{k+1} = p_k + v_{k+1}, \tag{21}$$

where v_k is the velocity, p_k is the particle position, c_1 and c_2 are acceleration coefficients, r_1 and r_2 are random constriction coefficients. In order to improve the quality of the training samples, the experimental data were preprocessed by Gaussian filtering. Detailed calculation and experimental results showed that this algorithm had better prediction performance (including accuracy, stability, and convergence rate) than simply utilizing a traditional BP neural network or GA. Similarly, a fuzzy hybrid of a PSO and gravity search algorithm was used to obtain the weight for training a neural network, so as to improve accuracy of the model [123]. Owing to the measurement noise of the RSSI, most fingerprint localization algorithms do not consider the weight of the optimized target point. Fang *et al.* [112] proposed a multi-objective evolution model to search for the optimal weight of targets through the filtered RSSI and the perceived noise covariance. The evolutionary model could find the optimal fingerprint estimation with the optimal weight, which was verified theoretically.

Intelligent algorithms can be used not only in fingerprint positioning systems based on WiFi, but also in visible light, sound waves, and other fingerprint signals for optimization problems. For example, Wu *et al.* [113] proposed a 3D visible light positioning system based on a DEA. The $Z_i(t)$ represents *i*th individual vector at generation *t*, randomly samples three other individuals for distinct *k*, *i*, *j* and *m*. Then, it generates a trial vector

$$U_{k,n}(t+1) = \begin{cases} Z_{m,n}(t) + F(Z_{i,n}(t) - Z_{j,n}(t)), & \text{if } rand_n < C \\ Z_{k,n}(t), & \text{otherwise.} \end{cases} \tag{22}$$

where *F* is a scalar parameter, and *C* is the crossover rate. If the new offspring has a better value, then selection operation is carried out

$$Z_i(t+1) = \begin{cases} U_i(t+1), & \text{if } f(U_i(t+1)) > f(Z_i(t)) \\ Z_i(t), & \text{otherwise} \end{cases} \tag{23}$$

where $f(\cdot)$ is the objective function to be maximized. The location model was considered as a global optimization problem by calculating the overlap areas of LED projection. DEA was only used to calculate the Z coordinates of the terminal. The process of dimension reduction from 3D to 1D greatly reduced the computing time. The experimental results showed that in an indoor environment of dimensions 4 m × 4 m × 6 m, the average positioning error reached as high as 0.69 cm, an in particular, the calculation time of a single point positioning was shortened to 24.26 ms. This indicates that the positioning algorithm had good practicability.

Guan *et al.* [114] proposed a 3D position estimation framework based on an improved GA by utilizing the global optimization ability of the GA. In contrast with other positioning technologies that utilize VLC, this system could achieve indoor 3D positioning without assuming the height or obtaining the azimuth of the mobile terminal. Macho-Pedroso *et al.* [115] proposed an optimization algorithm for indoor acoustic location, which used a GA to automatically estimate the optimal location of the microphone deployment. Different target performance metrics could be derived from the spatial likelihood function. The performance of this scheme was obviously better than manual work or randomly deployed sensors.

Park and Hashimoto [117] utilized an RFID navigation system to reduce the localization error of a mobile robot, it as an intelligent localization algorithm without the use of other sensors or systems which is modular and cost-effective. In particular, it could obtain about 10 cm location accuracy. RF signals have widely utilized in the field of activity recognition system, Sigg *et al.* [118] considered non-ad-hoc, active and passive, device-free activity recognition systems and proposed the DFAR for people without any wireless devices based on KNN and DT. For activities lying, walking, crawling and standing, the system can localise them within less than 1 m. Garcia-Valverde *et al.* [119] considered a fuzzy logic-based system which utilized an incremental learning method to adjust its behavior to the changing RSSI in ambient intelligent environments. The system also proposed a zero-cost localization algorithm which can achieve high accuracy in real-world spaces, and no prior knowledge of the access points locations and the environment was required.

To summarize, intelligent algorithms are not only applicable to the optimization problem, but also can solve the positioning problem. They can help to find the optimal location of the sensor deployment which is benefit for establishing more precise fingerprint maps [115]. However, the local optimal solution is usually got when intelligent algorithms are applied to solve the best setting parameters of ML algorithms, and it will lead to more time costs for localization. Therefore, we need to consider how to avoid the local optimal solution, not just optimization problem in the offline or online stage [117]. For the intelligent localization technology, the key is to choose the appropriate optimizer in the training stage for avoiding the local optimal solution. Here, we can consider the adaptive learning rate optimization algorithm (such as AdaGrad, Adam and RMSProp scheme [27]). And distributed machine learning algorithms can reduce the time cost and communication consumption.

In Table VII, the applications of the above intelligent algorithms in navigation and positioning are compared. In addition, intelligent algorithms are applied to UWB [124], RFID [116], and indoor robot navigation technology. These will not be discussed in any more detail here.

VI. Application Based Indoor Localization

This section discusses in detail the application of indoor positioning service in real life.

A. Positioning and Navigation of Indoor Environment

The cost reduction of external systems and heterogeneous sensor devices (such as WiFi and Bluetooth) enable mobile devices to obtain location data in a variety of ways. In some

TABLE VII
COMPARISONS OF DIFFERENT LOCALIZATION SYSTEMS BASED ON INTELLIGENT ALGORITHMS

Solutions	Category	Fingerprint	Method	Accuracy	Characteristics
Zhao [110]	Localization	RSSI	DE	N/A	The access point location optimization model improves the difference and diversity of signal strength array.
Moreno [111]	Navigation	Ultrasonic	GA	N/A	Genetic algorithm is used to design nonlinear filter for robot navigation.
Wang [112]	Localization	RSSI, RFID	PSO	<0.3824 m	PSO is combined with BP neural network, and Gaussian filter is used for preprocessing.
Fang [113]	Localization	RSSI	KF	<1.5 m	The multi-objective evolutionary model finds the best fingerprint by the optimal weight.
Wu [114]	Localization and trajectory tracking	Visible light	DE	0.69 cm	The 3D positioning system greatly reduces the calculation time.
Gua [115]	Localization	Visible light	GA	1.02 cm	The 3D positioning system does not need the information of height and positioning angle, and NN matches the nonlinear channel model.
Macho [116]	Localization	Acoustic	GA	<2.2 m	Determining the optimal position of the microphone before localization.
Wang [117]	Localization	RFID	PSO	<2 m	The improved intelligent algorithm is used to optimize the parameters of FNN model.
Park [118]	Localization and navigation	RFID	Read time	10 cm	A new orientation estimation method with only one antenna that uses two RFID tag coordinates.
Sigg [119]	Activity detection	RSSI	KNN, DT	<1 m	It distinguishes the transmitter is either under the control of the system or ambient.
Garcia [120]	Localization	RSSI	Fuzzy system	N/A	The adaptation localization system can accommodate the uncertainties and environmental changes.

large indoor scenes such as shopping malls, airports, hotels, convention and exhibition centers, museums and others, we can often see several LBSs [7], [125]. For example, when people shop in a mall, they can quickly find the place where they want to buy goods through location services, and they can also find shops or entertainment places of interest. In a complex airport indoor environment, navigation services can help people to get to the boarding gate quickly and accurately instead of by manual navigation. Indoor navigation can also solve the problem that people often cannot find their cars or parking spaces, owing to dark conditions and obstructions in underground parking lots. In convention and exhibition centers or museums, indoor positioning technology can provide LBS. People urgently need a positioning system in some cases for smart buildings. For example mobile phone navigation can allow employees to search for meeting rooms or indoor location sharing. Additionally, visitor management can track their trajectories through ID cards.

B. Nursing Personnel and Tracking

In nursing homes, people urgently need positioning and navigation services to provide personal safety. Location technology can achieve real-time monitoring of personnel and prevent loss. In the future, localization technology will be popularized in nursing homes and other places, which will be able to locate and query the motion trajectory for persons, and raise an alarm to provide location information and other services in the case of emergency. Moreover, such as smart phones allow users to determine the visibility of their location data, which indirectly increases users' confidence in LBS and protects their privacy. And there is also passive localization technology which means users do not carry any electronic device such as tags or sensors to track them [126]. The same technology may be applied to other scenarios, such as prisons and detention centers, which need to track the location of prisoners.

C. People Management

In underground mines, tunnels, chemical plants, and other construction scenarios, it is highly necessary to achieve the people management through localization technology. On the one hand, it is needed to locate the constructors and send out the distress signals when danger occurs so that rescuers can quickly arrive at the scene of the accident to ensure safety. On the other hand, real-time positioning is needed to alert personnel to dangerous areas to prevent entry when external personnel enter these scenarios. At present, most construction scenarios have certain positioning technology requirements. Especially, the environment information is completely unfamiliar for the blind users. The LBS combines other IoT technologies (such as RFID) to build a grid infrastructure for communications, blind children and adults can gain the independence and freedom to explore and participate in activities without external assistance [127].

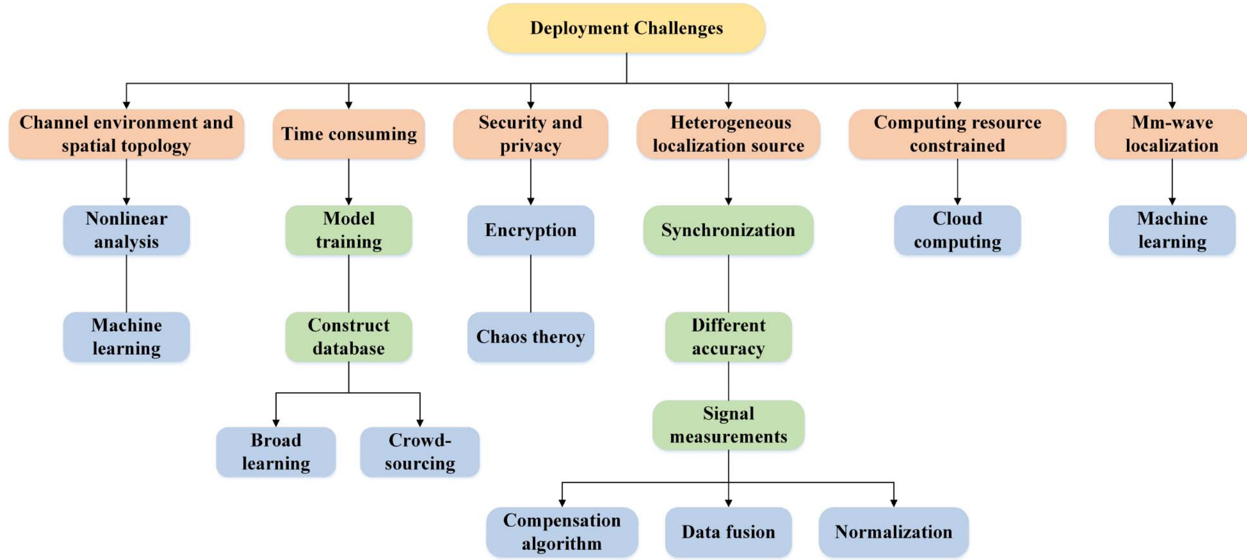

Fig. 4. Challenges and theoretical methods of indoor localization.

D. Fire Rescue and Other Safety Needs

Indoor positioning technology is widely applied in fire-fighting, emergency rescue, person searching, and other safety fields. When natural disasters, fires, and other emergencies occur, the system should determine the location of personnel in order to achieve the purpose of rapid rescue. And positioning technology combined with image recognition technology based on machine learning can quickly find the target, which helps the police station, fire brigade, healthcare center and disaster management systems to work together effectively [128]. In particular, it will become very difficult to determine the location depending on the rescue experience when an indoor scene undergoes collapse, layout changes, and other circumstances. When terrorist attacks or trampling incidents occur, commanders can determine the direction and location of human movement through positioning technology to facilitate emergency measures on the scene. Indoor positioning technology can provide strong technical support for rescue and national security applications, and better guarantee the safety of rescuers and trapped personnel.

VII. Challenges and Suggests

In this section, we discuss the problems of existing technologies based on the state of the art, and summarize the expected future trends in Fig. 4.

A. Complex Channel Environment and Spatial Topology

For radio frequency signals, line-of-sight communication between transmitter and receiver is a necessary prerequisite for positioning. Obstacle occlusion can lead to signal attenuation and even prevent the receiver from receiving the signal, such as when an IR signal cannot penetrate an obstacle. Satellite signals are transmitted from high altitudes, through the atmosphere to the ground, and then through barriers such as ground infrastructure, walls, and other obstacles to reach the receivers. The perceived signal intensity is very weak. Therefore, only high-precision receivers can be used, which not only increases the cost of positioning technology, but also leads to positioning accuracy within tens of meters.

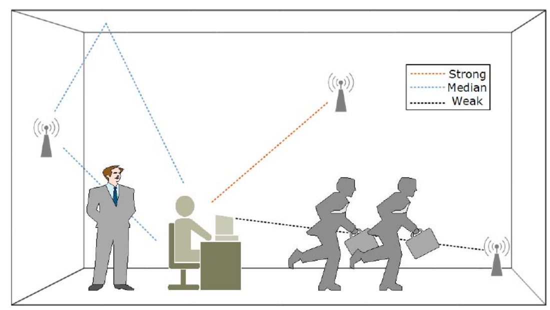

Fig. 5. Effects of indoor environment.

The complex topological relations of indoor environments are also the key factor leading to poor positioning accuracy. In an ideal environment, the transmission of signals is linear, such as the transmission model of RSSI signals. However, the geometric changes of an indoor environment and the spatiotemporal changes of signals become the biggest obstacles to the realization of high-precision positioning technology. As shown in Fig. 5, such changes include changes in pedestrian flow, the increase or decrease in signal transmitters, the change of furniture layout, and the refraction of signals through walls. Therefore, it is reasonable to believe that the transmission of signals is nonlinear in indoor environments. Indirectly, outdoor positioning technology is difficult to apply to indoor environments, and indoor positioning technology can only achieve the localization of local areas. This brings great difficulties in achieving indoor positioning technology for wide-area coverage.

In addition, in order to improve the ability of self-learning and self-adaptation to the environment, there is the problem of how to perceive the geometric changes of indoor environments and the spatiotemporal changes of signals. There is no uniform technical standard to realize automatic updating of fingerprint databases (such as a CSI database or visible light database) and electronic maps. Spatial topological relationships also bring many limitations of positioning accuracy and availability. This remains a scientific problem that has not been solved by indoor positioning technology.

B. Time Consuming

It takes a lot of time to collect and construct the fingerprint database and train the model, and the required time increases linearly with the number of measurements and the scale of the location environment. We consider that data can be collected dynamically by tracking user trajectories, but other techniques are also needed to reduce the training time. It would be preferable to utilize crowd-sourcing technology as the strategy to solve this problem. First, unsupervised learning is used to calibrate some crowd-sourcing data, and then the model is trained on the remaining crowd-sourcing data by semi-supervised learning. Therefore, this leads to a new problem, which is the labeling problem. Location labels used in positioning technology are a necessary condition for semi-supervised learning, and can be solved by a pseudo label method. It is well known that data must be labeled in the learning process, but the unlabeled data are not useless for the localization of regression. Apart from the additional data being utilized for data mining, the labeled data can also be combined with the unlabeled data to train the semi-supervised learning model. The implementation process of this method is simple and effective. In the actual operation, the labeled data are usually taken as the training set and the unlabeled data as the testing set. First, the labeled data are trained, and the trained model is used to predict the labels of unlabeled data, so as to obtain the pseudo labels. At this time, we can combine the original labeled data with the newly generated pseudo label data as new training data.

In view of the time-consuming problem of training the model, we believe that the BLS can be used as an emerging technical solution, which was proposed by CLP Chen and Liu [129]. The BLS is comparable to the network architecture of deep learning, which can solve the problem that a large number of parameters of deep learning need to be optimized. It is not necessary to retrain the model if the new data are input; it is only required to continue training the new data based on the original trained model. This method solves the problem in localization technology that the new collected fingerprint data should be fused into the fingerprint database to retrain the whole model, which takes too much time if the environment has changed slightly.

There are three layers in the BLS, which are the input layer, enhancement layer, and output layer. Only the enhancement layer is set with activation functions, and the other network architectures are linear. Given a training dataset $\{X, Y\}$ for localization, X is the fingerprint data and Y is the position (label), BLS employs sparse autoencoder for extracting features as

$$\arg\min_{\hat{w}} : \| Y \cdot W - X\|_2^2 + \lambda \left\| \hat{W} \right\|_1 \tag{24}$$

where $\hat{W}$ is the sparse autoencoder result, it is regarded as an optimization problem and utilizes regular l_1 and l_2 norm regularization. For n feature mappings ϕ_i, the mapped feature matrix is

$$Z_i = \phi_i(X \cdot W_{e_i} + \beta_{e_i}),\ i = 1, 2, \ldots, n \tag{25}$$

where W_{e_i} and β_{e_i} are weights and bias which are randomly generated and satisfy normal distribution; ϕ_i is an activation function, such as ReLu, sigmoid, linear and more. For the localization regression problem, we prefer the tanh function

$$y = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{26}$$

The enhancement layer further reinforces the m features of Z_i which can be updated as

$$H_i = \xi_i\big(Z \cdot W_{h_i} + \beta_{h_i}\big),\quad j = 1, 2, \ldots,\ m \tag{27}$$

where ξ_i is like ϕ_i. The output of enhancement layer is denoted by $H^m = (H_1, H_2, \ldots, H_m)$, then, the output of BLS is given by

$$Y = [Z^n | H^m] \cdot W^m \tag{28}$$

where W^m are the weights connecting to the output layer. It can be rapidly calculate by the ridge regression as

$$W^m = [Z^n | H^m]^+ \cdot Y \tag{29}$$

The system only needs a small number of calculations to get the updated weights by utilizing the last resulting and the new input data for the enhancement learning processing. Therefore, the training model of BLS is very fast. It has obvious advantages compared with the repeated training model and the local optimization of deep learning. At present, position technology is gradually applied to intelligent terminals and BLS can also solve the problem of limited computing power. It is reasonable to believe that BLS could have better applications in positioning technology in the future.

C. Security and Privacy

Location-based services bring great convenience to people in real life, but there is a problem that background applications can get the users' location information to expose their privacy for the profit of attackers. Cloud computing and edge computing are also widely utilized in positioning systems as new IoT technologies. They can solve the problems of resource and computing capacity constraints, and relevant localization algorithms are achieved by cloud services. Similarly, the fingerprint database, matching results, and other related positioning data used for training the model are transmitted from the cloud to terminal devices, which are vulnerable to attack. Security is also a consideration for cloud-related technologies. Existing positioning systems seldom consider security issues and pay too much attention to the positioning accuracy. Therefore, new security and privacy protection mechanisms are needed to ensure user safety and improve the service quality. Techniques related to cryptography can be used as an effective solution. In this paper, we propose the use of chaos theory, which can not only be used to solve nonlinear problems, but also has a natural relationship with cryptography.

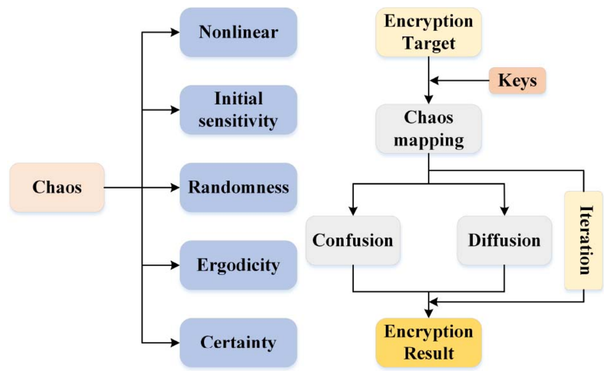

Fig. 6. Privacy measures of localization.

As stated above, the signal propagation model is nonlinear because of the interference of indoor environments. The common solution is to use the KF and particle filter for signal preprocessing and model training. The filtering problem at the state space is given by

$$\begin{aligned} x(k) &= g(k, k(k-1)) + \varepsilon(k) \\ z(k) &= h(k, x(k)) + \eta(k) \end{aligned} \tag{30}$$

where $\varepsilon(k)$ and $\eta(k)$ are the noise at the model and observation with a Gaussian distribution.

Chaos theory as a nonlinear subject, which has the basic characteristics of randomness, ergodicity, and certainty, and has been widely applied in the field of signal processing and control [130], [131]. The Logistic map is a classic chaotic equation which can be defined as follows

$$x_{n+1} = \mu x_n (1 - x_n) \tag{31}$$

where μ is the control parameter. In terms of its cryptosystem structure, a large number of encryption algorithms [132]–[134] have been proposed by combining the concepts of confusion and diffusion, as shown in Fig. 6. We believe that chaos theory will stand out as an effective solution in the future development of positioning technology.

D. Heterogeneous Localization Source

The location technology based on smart terminal takes smartphone as an example, and its location sources (i.e., signal transmitters) include three categories: satellite, radio frequency signal, and sensor. Satellite positioning is mainly based on GPS. Radio frequency signals include WiFi and Bluetooth. The intrinsic sensors of mobile phones include microphones, gyroscopes, magnetometers, light intensity sensors, cameras, and so on. The mechanisms and working principles of the three types of signal sources are different, the physical quantities and measurement method are different, and the measurement accuracies are also different, depending on the device and signal sources. In order to improve the positioning accuracy, it is necessary to fuse multisource heterogeneous signals to design the localization algorithm, which leads to the following problems:

1) Signal Measurements Vary From Terminal to Terminal: Different intelligent terminal devices have different measurement values for the same signal transmitter, and weak deviation is sufficient to cause the positioning accuracy error to be too large. For example, the positioning algorithm based on VLC [91] utilized four different types of smart phones to collect light intensity signals, and it found that the signal measurement values in the same area varied from device to device. It is worth exploring which device measurements are used to build the fingerprint database. Therefore, it is necessary to consider the hardware differences of intelligent terminal devices and establish a unified standard or processing algorithms to remove this influence. It is very important to achieve a localization technology of submeter accuracy.

2) Differences of Signal Measurement Accuracy: Theoretically, a good training model can be obtained to achieve high-precision positioning if the fingerprint database has high-accuracy signals and sufficient data. However, this becomes very difficult in practical applications. The fundamental problem is the accuracy of signal acquisition. Cheap sensors are susceptible to environmental factors such as temperature and humidity. For example, motion sensors with poor measurement accuracy cannot be directly used for inertial navigation. Furthermore, if a smartphone is used to collect signals, the distance and angle between the device and the signal source, or the movement of persons will interfere with the measurement accuracy. Large-scale coverage cannot be achieved owing to cost constraints if high-precision sensors are utilized. Therefore, the strategy of fusing signal sources of various precision can be adopted to improve the flexibility of algorithms such as [68].

3) Synchronization: The measurement process of different signal transmitters is independent, and the sampling time of different measurement values is also different. If a smartphone is used to estimate the location, the synchronization algorithm unifies all the measurements to the same time. If the localization processing is combined with cloud servers, we need to consider the problem of network synchronization. The error can be compensated or other methods to reduce the time synchronization accuracy of indoor positioning systems can be applied.

E. Computing Resource Constrained

The resource limitations of mobile terminal devices mainly include computing power, storage capacity, and life cycle. With the improvement of smartphone hardware, the computing power becomes more and more powerful, and there are many positioning algorithms based on smartphones. However, its computational power is limited, and its ability to implement complex ML or image processing algorithms is limited. As a multifunctional terminal, a mobile phones cannot use all the computing power for location algorithms. From the perspective of energy conservation, mobile phones cannot continue to run at high speed to process location algorithms; otherwise the battery would run out quickly. Owing to IoT technology, computing tasks of mobile terminals can be offloaded to nearby cloud servers. In order to extend the life cycle, mobile phones are only used to collect signals and receive positioning results.

F. Mm-Wave Localization

It is difficult to achieve high-precision localization due to the characteristic of WiFi in the large indoor environment. There will be a high cost and complex progress if we combine with other methods such as UWB. The millimetre wave band has attracted considerable attention with fine time resolution and interference mitigation. It can achieve millimetre-level accuracy based on RSSI and machine learning has been recently considered also for this field [135], [136]. Liang *et al.* [137] investigated the performance of ELM to use extensively in wireless communication applications such as millimetre wave band. And the proposed ELM-based positioning algorithm provides high precision and better robustness than existing techniques. We believe that millimetre wave band will play a key technology by intelligent localization in forthcoming 5G systems.

VIII. Conclusion

We contend that future positioning technology should be intelligent (with the abilities of self-learning and self-adaptation), and propose the architecture of intelligent localization. The architecture consists of four layers, one service, and one application. We provide a detailed overview of the indoor positioning technologies and systems based on wireless fingerprints presented in recent years. The fingerprint signals are divided into five types: RSSI, CSI, Bluetooth, magnetic field, and visible light. Their advantages and disadvantages, working mechanisms, and principles of localization are described. The different intelligent localization technologies (the applications of ML and intelligent algorithms) are compared in detail for different fingerprints, and we highlight their characteristics. In real life, positioning technology is widely used in personnel management, fire rescue, and other applications. Five types of technical development defects that need to be solved in the future are summarized based on the analysis of the existing positioning technology. Moreover, the BLS and chaos theory are proposed as corresponding solutions. We believe that this survey has certain significance as a reference and provides necessary information for the future development of intelligent positioning technology.

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