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Survey on CSI-based Indoor Positioning Systems and Recent Advances

Wen Liu, Qianqian Cheng, Zhongliang Deng, *(Senior Member, IEEE)*
Hong Chen, Xiao Fu, Xinyu Zheng, Shixuan Zheng, Cunzhe Chen, Shuo Wang
School of Electronic Engineering
Beijing University of Posts and Telecommunications
Beijing, China
Email:{liuwen, ambercheng}@bupt.edu.cn

***Abstract*—With the popularization of mobile devices, location based services (LBS) have received significant attention. Global Navigation Satellite System (GNSS) that widely used outdoors is unable to achieve high-precision positioning indoors, thus various indoor positioning methods are proposed for precise positioning. Wi-Fi based indoor positioning is widely used to provide accurate and efficient location services due to the convenience of hardware facilities. Channel state information (CSI) is an essential feature provided by Wi-Fi signals, which depicts the fine-grained features of channels, and attracts great attention in recent years. This paper comprehensively reviews the positioning technology based on CSI, and compares the primary positioning systems that makes great progress. This paper are mainly represented from two aspects: geometry-based positioning method and fingerprint-based positioning method. The former introduces angle-based method, range-based method, and the combination of both. The later mines the development process from traditional machine learning method to deep learning method. At the same time, this article also gives a brief overview of CSI's multi-source fusion technologies. Finally, this paper summarizes the challenges and points out the trends in this rapidly developing field.**

***Index Terms*—Channel state information (CSI), Indoor Positioning, IEEE802.11, localization techniques, recent progresses and comparisons**

I. Introduction

With the popularization of mobile devices, location based services (LBS) provide great convenience for smart cities, industrial production and people's daily lives. However, signal transmission in indoor environment is affected by multipath interference, shadow effect, power attenuation and transmission delay. Global Navigation Satellite System (GNSS) that widely used outdoors is unable to achieve high-precision positioning indoors [1-2], thus various indoor positioning methods are proposed[3-4] for precise positioning, such as Wi-Fi, Bluetooth, UWB and etc. Wi-Fi based indoor positioning is widely used to provide accurate and efficient location services due to the convenience of hardware facilities. It mainly consists of two categories: geometry-based method and fingerprint-based method. The geometry-based positioning method consists of angle-based method and range-based method. The former performs angle estimation by signals received from base stations whose locations are known [5]. The latter calculates position by measuring the distances between the target and multiple base stations [6-7]. The fingerprint-based positioning method mainly includes two parts: the offline part and the online part. The offline part mainly consists of data collection, preprocessing and fingerprint library establishment. The online part applies matching algorithm to the real-time signals to estimate the location of the mobile terminal.

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In the Wi-Fi based positioning method, RSS-based positioning is widely used due to its low computational complexity and strong applicability, such as: Horus [8], Radar[9]. However, RSS has the characteristics of low feature dimension and low spatial resolution, which leads to the problem of low matching accuracy [10]. With the application of the OFDM system and the MIMO system in the IEEE 802.11a/n protocol, CSI can be extracted from the commercial Wi-Fi device. Researches on indoor positioning [11], behavioral awareness[12], and target tracking [13] based on CSI have attracted wide attention. Compared with the signal strength information of RSS, CSI can provide multi-channel subcarrier phase and amplitude information to better describe the propagation path of the signal. Therefore, CSI has become one of the most commonly used feature in Wi-Fi based high-precision positioning.

In recent years, there are numerous reviews of Wi-Fi-based positioning methods [14-18], but most of these reviews are based on RSS. Meanwhile there are limited number of existing reviews on the CSI-based localization method. L.N.Kandel et al.[19] give an overview on the factors that lead to CSI measurement error, and summarized the error processing methods, but this survey missed the existing mainstream algorithms of CSI-based positioning. Therefore, this paper comprehensively reviews the CSI-based positioning methods, and introduces the major positioning systems that have great improvements in recent years. This article mainly consists of two aspects: 1) geometry-based positioning method and 2) fingerprint-based positioning method. The geometry-based positioning includes angle-based method, range-based method, and the combination of angle and range information. The fingerprint-based positioning includes traditional machine learning method and deep learning method. At the same time, we also give a brief overview on CSI's multi-source fusion approaches. Finally, this paper compares and summarizes primary CSI-based sys-

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tems in detail.

Our paper makes notable contributions summarized as follows:

1) This survey provides the most comprehensive overview of CSI based indoor localization methods. For each type of positioning method, we introduce the improvements in detail, and summarize the existing systems.

2) This survey provides abundant resources on CSI based indoor localization methods, which includes state-of-the-art algorithms and systems. This paper can be used as a hands-on guide for understanding, using, and developing methods used in different scenes.

3) This paper summarizes the challenges faced by CSI-based positioning and points out the possible directions in this rapidly developing field.

The rest of this survey is organized as follows. Section II introduces the physical meaning and mathematical formulation of CSI. Section III summarizes the existing CSI positioning methods from two aspects: geometry-based method and fingerprint-based method. Section IV introduces the existing CSI-based homology and multi-source fusion technology. Section V summarizes the paper.

II. Preliminaries of CSI

In a Wi-Fi network, signals are propagated through OFDM modulation. OFDM divides the communication channel into orthogonal sub-channels of different frequencies, and signal is received by the terminal after being transmitted through the multipath channel. CSI represents the characteristics of the communication link between the transmitter and the receiver. It not only reflects the attenuation of the wireless signal during propagation between the transmitter and the receiver, but also reflects the scattering and refraction encountered by the signal during transmission. The data packet received by the receiving end includes information such as time stamp, RSS, number of antennas, noise, and CSI. Channel status information can be expressed as:

$$Y = HX + N \tag{1}$$

Where Y is the received signal vector, X is the transmitted signal vector, H is the channel information matrix, and N is additive white Gaussian noise, so CSI can be expressed as:

$$\widehat{H} = \frac{Y}{X} \tag{2}$$

$\widehat{H}$ is the CFR (channel frequency response) of each sub channels.

To describe the multipath effect, the channel impulse response (CIR) can also be used to represent the channel. Under the assumption of linear time-invariant, the channel impulse response can be expressed as:

$$h(\tau) = \sum_{i=1}^{N} a_i e^{-j\theta_i} \delta(\tau - \tau_i) \tag{3}$$

a_i,θ_i,τ_i represent the amplitude, phase, and delay of the i-th path of the signal propagation, respectively, N is the number of multi paths, and $\delta(\tau)$ is the pulse function. Under the condition of infinite bandwidth,CFR is the Fourier transformation of CIR.

The phase received by the k-channel subcarrier of channel i is usually expressed as:

$$\varphi_{i,k} = \theta_{i,k} - 2\pi \cdot k \cdot f_s \cdot \sigma_i + \beta_i + Z \tag{4}$$

In IEEE 802.11n, k varies over a range of -28 to 28 under 20 MHz bandwidth (index 0 is reserved for carrier frequency), $\theta_{i,k}$ represents the true phase, and σ_i is the time offset of the receiver relative to the transmitter (including time shift caused by PDD and SFO), f_s is the interval between two adjacent subcarriers, which is 312.5KHz; β_i is the unknown phase offset; Z is the additive white Gaussian noise.

III. CSI-Based Positioning Methods and Systems

A. Geometry-Based CSI Positioning

1) Angle-Based Approaches: Angle measurement technology based on array signal can be well applied to angle-based CSI positioning. We can estimate the AOA by combining the phase information in the CSI measurements on the Wi-Fi device according to the array antenna angle measurement technique.

The MUSIC algorithm proposed by Schmidt et al. [20] works well in resolution, estimation accuracy and stability under the condition of multi-sensor or multi-antenna. However, the number of antennas for commercial WiFi devices is generally limited, and indoor multipath is severe. In 2013, Xiong J et al.[21] implemented the ArrayTrack hardware platform for CSI indoor positioning. The platform uses 6-8 antennas, among which the authors use key mechanisms such as spatial smoothing, array geometric weighting and AOA spectrum synthesis to accurately estimate AOA. This method has the positioning accuracy of 30-50 cm. In 2013, Gjengset et al. [22] proposed the Phaser system, which actually leverages CSI amplitude and phase data for angle measurement based on array signal. The system expands the number of antennas to five and eliminates the phase difference between the different network cards by sharing one antenna, and the average positioning error is less than 1 m. In 2015, Kotaru et al. [23] proposed the SpotFi system, which uses phase measurements from different subcarriers, increasing three antennas to 3*30 sensors. SpotFi employs CSI smoothing method to approximate enough independent measurements to implement the super-resolution AOA estimation Technique, and utilizes the likelihood algorithm to identify whether there is a direct path, and determines the AOA of the target to the AP. The SpotFi system is capable of positioning accuracy with an average error of 40 cm, and with only two direct paths between the target and the AP, the median positioning error is 1.6 meters, which is better than ArrayTrack. In 2019, Zhang et al. [24] proposed 3D-WIFI, which is a three-dimensional indoor positioning system. 3D-WiFi adopts an L-shaped array in the angle measurement. 3D-WiFi proves that the AOA estimation accuracy using the sparse reconstruction algorithm is better than the MUSIC algorithm. And it can obtain decimeter-level three-dimensional positioning accuracy in an open indoor environment.

CSI-based AOA estimation mainly utilizes a clear relationship between the phase difference of the signals received by each antenna on the AP. By increasing the number of antennas, the effects of multipath effects can be alleviate. However, current commercial Wi-Fi is usually not configured with more antennas, and the validity of the utilized CSI phase information will affect the accuracy of the positioning results directly.

2) Range-Based Approaches: In consideration of the severe multipath effect and shadow effect in the indoor environment, the positioning method based on RSS has large ranging error. Moreover, in the practical application, due to the influence of various factors, such as human movement and environmental noise, the RSS value fluctuate greatly, which further affect the accuracy of positioning. In order to overcome the weak time stability and the low positioning accuracy of RSS ranging, researchers focus their attention on CSI.

In 2012, Wu et al. [25] implemented the FILA system. They process the CSI's amplitude into the valid value, CSI_{eff}. Then, they develop a fast training algorithm based on supervised learning to derive the relationship between CSI_{eff} and distance, and furtherly build a refined indoor propagation model. FILA achieves median accuracy of 0.45 m in the research laboratory, 1.2 m in the university lecture theatre and 1.2 m in the corridor environment. In 2018, Kotaru et al. [26] presented WiCapture, a novel VR position tracking system. They develop a wireless channel model that takes account of change in channel and phase distortion due to displacement and frequency offset. By estimating Angle of Departure (AoD) and loss of all the paths, WiCapture estimates the displacement of the transmitter during the time between consecutive CSIs. It achieves a median trajectory error of 0.88 cm in indoor office deployment, 1.51 cm in occlusion deployment and 0.85 cm in outdoor deployment. In 2018, Wang et al. [27] presented LiFS, an accurate model-based device-free localization system with low human effort. LiFS adopts different methods to pre-process the raw CSIs according to whether the target is present in the First Fresnel Zone (FFZ) and then formulates a power fading model (PFM) equation. By solving a set of PFM equations formulated for all the paths, LiFS can estimate the target location accurately. LiFS achieves a median accuracy of 0.5 m and 1.1 m in Line-of-Sight (LoS) and Non-Line-of-Sight (NLoS) scenarios respectively. In 2019, Han et al. [28] proposed S-Phaser, an indoor localization system that uses a single Wi-Fi AP to locate terminals. They propose the Interpolation Elimination Method(IEM) to eliminate phase and angle error. Then, they use the Broadband Angle Ranging (BAR) to estimate transmission distance and apply triangulation to determine the user's location. S-Phaser achieves 1.5 m localization accuracy in the LoS environment.

By effectively preprocessing CSI, researchers developed more accurate and robust wireless channel models to estimate the distance between mobile devices and APs. Considering that CSI reflects the power attenuation of signals in the process, the multipath effect is suppressed and the positioning accuracy is improved.

3) Fusion of Angle and Range Approaches: Considering that single positioning method based on either angle measurement or range measurement has its own advantages and disadvantages, researchers focus their attention on fusion of angle and range measurement.

In 2017, Han et al. [29] presented a new indoor localization approach by employing just single AP to get an accurate location of user's terminal. They receive CSI from different channels and use the interpolation elimination algorithm to eliminate the phase error in the CSI. Then, they employ the spatial smoothing algorithm to process the CSI , and estimate the value of AOA and TOA which is used to identify the direct path by LOS clustering algorithm. This method reaches the median error of 0.6 m when the environment is static and has direct path. In 2018, Ahmed et al. [30] proposed a modified matrix pencil (MMP) algorithm, to estimate AoA and time of flight (ToF) for all dominant multipath components from Wi-Fi CSI data. A multi-packet CSI aggregation method that uses the CSI values from several packets to improve accuracy and speed is proposed. MMP performs around 200 times faster than a two-dimensional version of the multiple signal classification (2D-MUSIC) algorithm with the same estimation accuracy. In 2018, Zhang et al. [31] developed DeFi, a novel robust training-free device-free localization (DFL) system. By using a background elimination algorithm, they eliminate the static paths and separate out the target reflection path from the motion paths according to the AoA and equivalent ToF measurements. With the AoA of the target reflection path as observation information, DeFi estimate the target location based on a particle filter algorithm. DeFi achieves a median error of 0.57 m in the laboratory and 0.34 m in the lobby.

B. Fingerprint-Based CSI Positioning

Fingerprint localization is a method of using the acquired signal features to correlate with specific locations within a room. Compared with positioning technologies such as AOA and TOA, fingerprint positioning technology has the advantages of easy implementation, high precision and flexible algorithm. Wi-Fi is widely used in fingerprint localization technology as an easily available signal source. Wi-Fi fingerprint positioning usually consists of two phases: offline phase and online phase. In the offline phase, fingerprints at various locations are collected to build a fingerprint database. In the online phase, the system will receive the signal characteristics to match the signals in a database. The schematic diagram is shown in Figure 1.

1) Fingerprint Pre-processing: For fingerprint feature extraction, the more feature dimensions are used, the richer the location information is. Compared to traditional RSS, CSI contains information on two dimensions, amplitude and phase. In 2014, Chen et al. [32] leveraged RSS, transmission power and CSI to construct fingerprints, 90% of the detection points

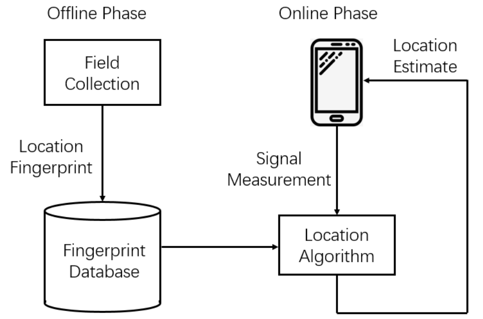

Fig. 1. Fingerprint positioning principle block diagram

of this scheme can reach the accuracy within 2 meters under the condition of disordered indoors. In 2019, Dang et al. [33] proposed a passive human indoor positioning method called FapFi, which combines CSI amplitude and phase information. In the offline phase, the redundancy values and outliers are filtered out, and then a linear transformation is applied to extract the calibrated phase information. This method can achieve average positioning accuracy of 0.5m and 1.2m in laboratory and conference rooms.

The acquired CSI sample matrix has a high dimensional characteristic, which greatly enriches the fingerprint database and facilitates more accurate position estimation. However, for high-dimensional CSI fingerprint samples, the severe problem is that the large fingerprint database and the high time complexity. Therefore, after collecting high-dimensional fingerprint samples, it is usually necessary to reduce the dimensionality [34] and [35] propose to use principal component analysis (PCA) or linear decision analysis (LDA) to filter the most relevant feature vectors and reduce the number of dimensions. In 2014, Chapre et al. [36] proposed CSI-MIMO Indoor Wi-Fi Fingerprinting System, in which the CSI value obtained in the configuration of the multiple transmit and receive antennas is reduced by dimension to 1×30: $CSI_{avg} = \sum_{m=1}^{p} \sum_{n=1}^{q} csi_{mn}$. Where, p and q respectively represent the number of transmitting and receiving antennas. The above method further improves the positioning efficiency.

2) Fingerprint Matching: Both the deterministic algorithm and the probabilistic algorithm are applicable in the online matching phase of CSI fingerprint location. In 2017, Xiao et al. [37] proposed a KNN localization algorithm based on Kullback–Laibler gradient. Zhao et al. [38] adopted a kernel-based WKNN localization algorithm. Wu et al. [39] proposed a localization algorithm applying improved naive Bayesian classifiers with confidence. The above methods can achieve positioning accuracy within an average of 2m. In 2018, Shi et al. [40] proposed a fingerprint-based device-free passive indoor position tracking system, which leverages the CSI amplitude to construct fingerprint samples. In the online stage, the author uses Bayesian filtering to recursively predict the coordinates of moving objects, so as to track the trajectory of moving subjects. The positioning accuracy of the scheme is less than 1m in the messy interior.

3) CSI Fingerprinting Systems: Since CSI fingerprint positioning technology has the characteristics of high accuracy, low cost, flexible algorithm and easy implementation, varied CSI fingerprint positioning systems have emerged in recent years. In 2012, Xiao et al. [41] first proposed FIFS, an indoor fingerprint positioning system based on CSI. The system first processes the original CSI value by frequency diversity and space diversity, uses the probability model to map the CSI value into a fingerprint and constructs a fingerprint database. FIFS has higher positioning accuracy than Horus system, and the average error is less than 1m in unmodified FIFS WLAN network deployment. However, FIFS only uses the amplitude characteristics of CSI, and the amplitudes measured on multiple antennas are simply averaged to obtain fingerprints, the characteristics of frequency diversity are not fully utilized. In 2016, Chen et al. [42] proposed a fingerprint-based Wi-Fi-TRIPS(Wi-Fi based time-reversed indoor positioning system). In the offline phase, the CSI collected in the 10 MHz band is processed. After the timing and frequency synchronization errors are compensated, the fingerprints are connected into 1GHz fingerprints and stored in the database.. In the online phase, the TR resonance strength is calculated using the stored fingerprint and the fingerprint from the test point to perform position estimation. This system can achieve a precision of 5 cm in a small area of 20 cm x 70 cm in an NLOS office environment with only one link. In 2019, Zhang et al. [43] proposed a positioning system using only one AP. They used a new phase decomposition method to obtain multipath phase information and applied a linear transform algorithm to eliminate noise in the phase. The system achieves the average accuracy of 0.6m in laboratory, 0.45m in conference room and 1.08m in corridor.

In recent years, CSI fingerprint-based positioning technology attracts wide attentions in the field of indoor positioning because of its high precision. However, as the scale of database increased, the training cost and processing complexity will be greatly raised. The application of deep learning to extract CSI data features and training data can improve fingerprint acquisition and matching efficiency and positioning accuracy. We will introduce the CSI positioning technology based on deep learning in III.C in detail.

C. Learning-Based CSI Positioning

There are many difficulties in CSI fingerprinting localization, such as large scale of database and high computational cost etc. As a method that could learn from experience, machine learning is increasingly employed in the processing of CSI. Machine learning algorithms for localization could be divided into two main categories, traditional machine learning and deep learning.

1) Traditional Machine Learning Approaches: Traditional machine learning algorithm performs well in classfication problems, such as K-nearest neighbor (KNN) and weighted K-nearest neighbor (WKNN)[44-47], support vector machine (SVM)[48-49], random forest (RF) [50-51], naive Bayesian classification [39][52], and so on.

KNN chooses K Reference Points (RPs) with the largest similarity and calculates the average coordinate as the result. WKNN could optimize the result of KNN by adjusting the weights of the K points. KNN and WKNN are often combined with various data pre-processing methods to improve the localization accuracy. In 2017, Zhao et al. [45] proposed a localization system, which applied the time domain filtering and a dimensional reduction method based on coherence bandwidth to the CSI data, then utilized an improved weighted k-nearest neighbor algorithm based on kernel methods for position estimation. The positioning error is less than 2m in 70% of the test points. Support Vector Machine (SVM) is an algorithm for classification or regression. It could obtain the optimal decision boundary by searching for the largest edge hyper-plane. It performs well in solving high-dimensional and nonlinear classification problems. In 2017, Zhou [48] proposed a system that employed SVM classification in device-free detection and localization. First, spatial clustering and PCA dimensionality reduction are applied to CSI data to remove random noise and extract effective features .Then SVM algorithm is employed to get the estimated position.

Random forest defines a classifier that consists of multiple decision trees. In 2018, Wang et al [50] proposed a novel solution to the feature extraction in a complex environment. Multiple decision trees are constructed, and the trees are pruned based on the root mean square error. With the votes from the decision trees, the estimated result could be obtained. Bayesian classification is a classification algorithm based on knowledge of probability statistics. In 2018, Wu [39] proposed an improved Bayesian positioning method for the problem of large environmental noise and multipath effect in device-free positioning. The average and standard deviation for different subcarriers are calculated to generate a fingerprint database. The improved naive Bayesian classifier combined with the confidence is applied to compare the pre-processed CSI data with the database to obtain the estimated position. The system could achieve a classification accuracy of more than 90% on average.

For both of KNN and WKNN , the algorithms directly search the whole database instead of 'learn' for it, which would increase the computation cost. SVM could accurately simulate high-dimensional and nonlinear functions, but it takes a long time for training. The random forests algorithm has a better visualization effect and lower calculation complexity, while it is has the problem of over-fitting. The Bayesian method which is convenient to implement with high process speed, performs well for multi-classification. In fact, it has the assumption that the distribution is independent, which doesn't conforms to the reality.

2) Deep Learning Approaches: The application of machine learning could improve the positioning accuracy, enhance the robustness of the system and reduce the cost . In addition to the traditional machine learning mentioned above, CSI positioning technologies based on deep learning have become a new development trend. Deep learning approaches extract CSI data features and find the functions between data and locations. Different from traditional methods, the neural network could extract high-order features without additional feature engineering. For projects with big data, deep neural networks could increase the system accuracy to a large extent. Thus the deep learning improves the system from the aspects of positioning accuracy and stability.

CSI could be combined with deep neural networks. In 2015, Wang [53] et al. proposed DeepFi system which leveraged CSI amplitudes in deep learning. First, the features of the original CSI amplitudes are extracted by the deep self-encoder, and the weights of the self-encoder are recorded as a new fingerprint. The positioning error is 0.94m in the open environment and 1.80m complex environment; In 2016, PhaseFi system [54] has been proposed which also employs the deep self-encoder to extract the features of calibrated phase data. The positioning errors is 1.08m in the open environment and 2.01m complex environment. The neural network can also be directly applied in the classification and regression stages. In 2017, Wang proposed CIFI system [55] in which the convolutional neural network was employed to train and classify the estimated AOA images. The images were calculated from the calibrated CSI phase. For the convolutional neural network could extract image features better, the performance is better than DeepFi and PhaseFi. In 2019, Hsieh et al. [56] proposed 1D-CNN network based on the idea of classification ,which employed multiple one-dimensional convolutional layers to process CSI amplitude and RSS. Besides, various experiments have been conducted to compare the positioning accuracy in MLP-RSS, MLP-CSI, CNN-RSS, CNN-CSI models, and it was found that 1D-CNN could maintain high accuracy with much less network parameters.

The above systems are models that only leverage single feature of CSI. In fact, the neural network could also process multiple features of CSI at the same time. Compared with systems utilizing single feature such as DeepFi, PhaseFi, and CIFI., these systems could utilize the amplitude and phase of CSI simultaneously, to improve positioning accuracy. For example, BiLoc system [57] applied a deep learning-based algorithm to exploit bi-modal data, i.e., estimated AOA and average amplitudes for both the off-line and online stages. ResLoc system [58] leveraged dual-channel CSI tensor data to train a deep network using the proposed deep residual sharing learning approach, and the positioning accuracy is further improved. In addition, the neural network and CSI could also be utilized in channel state recognition (LOS and NLOS) [47], human body trajectory tracking [59] etc. Choi JS et al. [47] proposed to apply the cross-layer information of RSS and CSI to deep recurrent neural network (RNN) for channel identification. This method of RNN is superior to traditional methods based on path power skew, peak and phase distribution, which is important for further accurate positioning.

The application of machine learning could better mines the fine-grained channel information and improve the positioning accuracy. It could extract ample features and reduce the scale of database, then further reduce the calculation complexity.

TABLE I
COMPARISONS OF POSITIONING SYSTEM

Name	Time	Method	CSI Information	Experimental environment and positioning accuracy
FIFS[41]	2012	Fingerprint	Amplitude, Phase	Laboratory and Corridor; $\leq$ 1 m
FILA[25]	2012	Range	Amplitude	Laboratory, Reading Room and Corridor; $\leq$ 3 m
Pilot[63]	2013	Fingerprint	Amplitude, Phase	Laboratory and hall; $\leq$ 2 m
CSI-MIMO[36]	2014	Fingerprint	Amplitude, Phase	Laboratory 1.53 m; Meeting Room 1.78 m; Corridor 3.15 m;
DeepFi[53]	2015	Fingerprint	Amplitude	Living Room and Laboratory; $\leq$ 2 m
PhaseFi[54]	2016	Fusion of angle and range	Phase	Bedroom and Laboratory; $\leq$ 2 m
BiLoc[57]	2017	Fingerprint	Amplitude, Phase	Laboratory 1.57m;Corridor 2.15 m;
CiFi[55]	2017	Angle	Phase	Laboratory 40% $\leq$ 1 m, 87% $\leq$ 3 m; Corridor 60% $\leq$ 3 m;
ConFi[64]	2017	Fingerprint	Amplitude	Living Room and Laboratory;1.37 m;
ResLoc[58]	2018	Angle	Amplitude, Phase	Laboratory 0.89 m; Corridor 1.24 m;
DeFi[31]	2018	Fusion of angle and range	Phase	Living Room and Laboratory; 0.6 m
LiFS[27]	2018	Range	Amplitude	LOS 0.5 m; NLOS 1.1 m;
S-Phaser[28]	2019	Range	Amplitude, Phase	Laboratory; 1.5 m
System Zhang et al. proposed[43]	2019	Fingerprint	Phase	Laboratory 0.6 m;Meeting Room 0.45 m; Corridor 1.08 m;

Among these machine learning algorithms, deep learning are are especially works well in handling big data.

D. Table of Positioning Systems

As shown in TABLE I, comparisons of 14 representative positioning systems are given. The typical indoor environments are mainly include laboratory, corridor, meeting room and living room.

IV. CSI POSITIONING BASED ON DATA FUSION

The data fusion based positioning method can be divided into homologous data fusion positioning and multi-source data fusion positioning.

A. Approaches Based on Homogeneous data fusion

In the homologous data fusion positioning, by combining different characteristics of information from the same signal source, the positioning accuracy can be further improved. In 2014, Jiang et al. [60] proposed C^2IL, which utilizes unsupervised learning to establish a mapping relationship between CSI-RSS fingerprints and locations. The CSI is used to estimate the moving speed of the wireless device and the RSS fingerprints are utilized for ranging. Positioning and tracking are achieved by combining the information of the two aspects. The system can achieve positioning error within 2% within 80% of the time in a messy indoor environment. In 2017, Zhao et al. [38] proposed a method of fingerprinting using RSS and CSI data from a single AP. They reduce the instability of CSI values caused by multipath effects by preprocessing CSI with time domain filtering. This scheme can achieve a positioning accuracy of 1.79 meters in a typical laboratory, which is superior to FIFS and Horus.

B. Approaches Based on Multi-source data fusion

In the multi-source data fusion positioning, the characteristic provided by other signal sources (such as images, IMUs, etc.) can be combined with CSI to provide more information. Motion state and LOS condition can assist positioning and improve positioning accuracy. In 2016, Li et al. [61] proposed an enhanced particle filter based positioning method that combines CSI information and inertial sensor information to achieve high precision tracking. The distance and velocity information are estimated using CSI and IMU, respectively. In a messy environment, the proposed tracking method has an average accuracy of 1.3m, which is more accurate and stable than pedestrian dead reckoning (PDR) and ranging positioning. In 2017, Huang et al. [62] proposed a hybrid fingerprint localization algorithm by combining CSI and magnetic field strength. First, CSI data from multiple APs are used to discriminate LOS/NLOS. Then, the CSI and magnetic field information are combined to construct a fusion fingerprint database, and a multi-dimensional scale KNN algorithm is applied to estimate the location. This algorithm achieves less than 2 meters localization accuracy with 80% confidence in the office.

In summary, the positioning method based on RSS and CSI fusion can alleviate the low robustness of CSI-based positioning system caused by indoor multipath. The introduction of redundancy method can effectively reduce the computational complexity of CSI positioning. However, in the indoor dense cluttered environment, the single source positioning method based on Wi-Fi wireless signals still faces problems such as dense signal reflection, human body occlusion, and electromagnetic interference. The CSI positioning method based on multi-source information fusion can effectively deal with the above various interferences by introducing heterogeneous features such as IMU, geomagnetism and image, which can improve the accuracy and robustness of the CSI positioning system. In the process of reviewing the literature, the authors found that most of the CSI positioning methods based on multi-source information fusion directly combine the CSI features , IMU and other heterogeneous features to form a hybrid fingerprint, which does not fully realize the complementary advantages between heterogeneous features. With the development of machine learning technology, it is foreseeable that in the future, the tight coupling and fusion positioning of multi-source information based on machine learning is one of the development trends in CSI positioning technology.

V. Conclusion

In this survey, we conduct a comprehensive overview of CSI-based indoor localization methods. For each type of positioning method, we introduce the improvement of the algorithm in detail. We provide a thorough review, comparisons, and summarizations of primary systems proposed in recent years. Finally, we summarize the challenges faced by CSI-based positioning and point out the possible directions in this rapidly developing field. This paper can be used as a hands-on guide for understanding, using, and developing methods used in different scenes.

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