Research on CSI Indoor Fingerprint Location Algorithm Based on Adaptive Kalman Filter

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Abstract: In order to improve the indoor positioning accuracy and stability of WiFi received signal strength indicating (RSSI), we propose a channel state information (CSI) indoor fingerprint location algorithm based on adaptive Kalman filter in this paper. In the offline stage, the original data is filtered by adaptive Kalman filter algorithm with variance compensation, and then the filtered data is classified by binary K-means clustering algorithm. Then, according to the off-line data and real-time data of the point to be measured, the K nearest neighbor matching algorithm is used to estimate the location coordinates of the location point in the online stage. Finally, simulation and field experiments show that the algorithm can effectively reduce the influence of multi-path attenuation at the receiving end of the signal by using the amplitude characteristics of the corresponding subcarriers in the channel, and the positioning accuracy reaches 0.7m. In addition, the positioning results are efficient and effective.

1. Introduction

At present, most of the localization methods obtain the location information of the target by matching the RSSI value of the acquisition signal with the fingerprint database. However, because the RSSI is coarse-grained information, it is affected by the refraction, reflection and diffraction of the signal caused by the indoor environment and so on, resulting in the unstable localization performance. In recent years, some commercial wireless network card devices can support the collection of channel state information (CSI) in physical layer, such as intel5300, atheros9380. Because different subchannels of CSI can extract more fine-grained feature signals than RSSI for analysis, and CSI can avoid the influence of multipath effect and noise as much as possible, in additon, there are many indoor positioning[1] research results.

Compared with RSSI positioning, CSI changes little with time and has higher sensitivity. Using the information of signal transmission process of different subcarriers can better resist the problem of noise and multipath effect. The fine-grained CSI fingerprint method can improve the precision of indoor positioning and effectively improve the accuracy of indoor positioning[2] without increasing the cost of data acquisition.

Due to the complexity of indoor environment, such as many objects, personnel flow and multipath effect on signal propagation. However, CSI can better reflect these characteristics, so CSI own higher applicability in indoor positioning field[3]. In the literature[4], combining CSI and RSSI data as fingerprint features, introducing the idea of spatial clustering to process the collected data, effectively reduced the time-varying signal and the overall average positioning error. FIFS scheme proposed in the literature[5] was to use the CSI raw data of multiple antennas in time and frequency domain, consider the path loss and improve the positioning accuracy. In the CSI-MIMO scheme proposed in the literature[6], the original CSI data was collected by using the spatial difference attribute of multiple antennas, and the spatial attribute of multiple input CSI was used for positioning. In the literature[7], CSI signal was effectively reduced by sparse representation in frequency domain, and the influence of multipath effect on positioning accuracy was solved to a certain extent. In the literature[8], Cheng Yue and others proposed to use the multi-sensor location

information to screen the reference nodes of fingerprint database, and retain the effective reference nodes to improve the positioning accuracy; In the literature[9], Xuyu Wang and others proposed to train CSI data as fingerprint database through deep learning, which significantly improved the positioning accuracy. However, the training samples of this method in the offline data collection stage were too large and took too long.

Summarizing the advantages and disadvantages of common fingerprint location methods, it can be seen that solving the data preprocessing and extracting effective feature value in the indoor fingerprint location algorithm are the main factors to improve the location accuracy. In order to achieve the goal of high efficiency, high accuracy and high adaptability of indoor location, this paper proposes a CSI indoor fingerprint location algorithm based on adaptive Kalman filter. In the off-line phase, the location is divided into approximately equal size area blocks. CSI signals are extracted from Atheros 9380 wireless network card which supports 802.11n protocol. Fingerprint data is sampled at each connection point, filtered and stored in the original information base. Then the filtered data is classified into fingerprint numbers using binary k-means algorithm Database; In the online stage, according to the offline data and real-time data of the point to be measured, KNN matching algorithm is used to determine the location coordinates of the point. The core idea of KNN matching algorithm is to dynamically adjust the algorithm to solving the problem[10] of filtering divergence through the adaptive Kalman filter processing of variance compensation of the offline data, so as to make the establishment of fingerprint database more effective, smaller range, and improve matching accuracy and positioning accuracy.

2. Location model and algorithm

2.1 Fingerprint location model

The indoor environment is characterized by a great many rooms, obstacles and frequent flow of people. Assuming that the area to be tested is completely covered by wireless WiFi network, and we select uniform reference points during signal acquisition and record CSI values of all AP points. Based on OFDM technology, the channel can be modulated into multiple orthogonal subchannels[11] and the high-speed data signal can be converted into parallel low-speed data stream. Therefore, in data acquisition, the CSI value of each subchannel can be collected as reference information after filtering the single channel information. The method based on fingerprint database location consists of two basic phases: offline training and online location. The location model is shown in Figure 1.
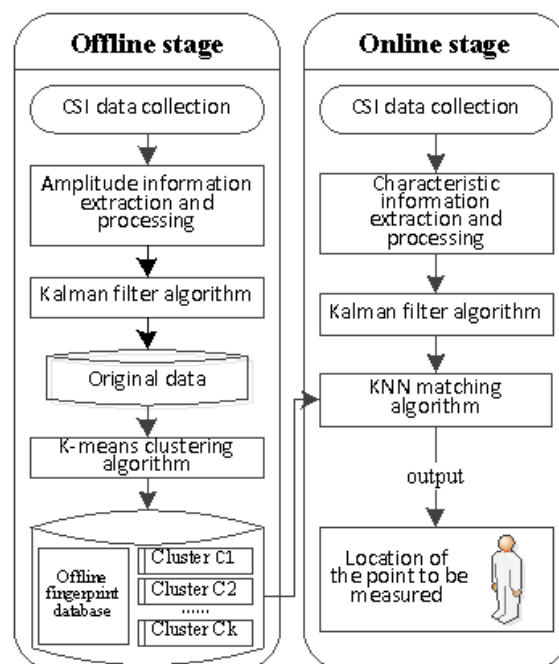

Figure 1. Model of data processing based on CSI

Offline stage: The location site is approximately divided into equal size blocks. At each connection point, we collect the CSI value of a single channel by OFDM technology to extract amplitude information, on this basis, we use the adaptive Kalman filter algorithm of variance compensation to denoise the extracted feature data, and store the denoised data to the original information database, and then use the binary K-means clustering algorithm to do Cluster analysis of the original data, later we reduce the feature data with the same characteristics to a certain area, finally, we form the off-line database of cluster shape as the fingerprint point data to establish the feature fingerprint database.

Online stage: we obtain the unknown CSI eigenvalue of AP dynamically at the location to be tested, process the data through adaptive Kalman filter algorithm, and use KNN or Bayes algorithm to process the data and fingerprint database information in real time for matching calculation. Since this paper is aimed to study the influence factors of offline data established on CIS location algorithm, we use the KNN matching algorithm which is more mature to estimate the location of location points.

2.2 Adaptive Kalman filter algorithm

The adaptive Kalman filter algorithm[12] has the ability of dynamic data processing, that is, it can estimate and modify the unknown or uncertain system model parameters in the process of data filtering. By using the existing information to estimate the dynamic noise variance in real time, it can compensate the deficiency of dynamic variance or covariance in the filtering. This method uses the prediction residual to modify the original vector. The method of calculating the actual state vector is called the variance compensation method of adaptive Kalman filter. The basic ideas are as follows:

The Kalman filter state equation and observation equation of discrete linear system can be expressed as

$$\begin{cases} X_{k+1} = \Phi_{k+1,k} X_k + \Psi_{k+1,k} U_k + \Gamma_{k+1,k} \Omega_k \\ L_{k+1} = B_{k+1} X_{k+1} + Z_{k+1} + \Delta_{k+1} \end{cases} \tag{1}$$

In the statement, X_{k+1} and X_k are the filtering values of the state vector at time t_{k+1} and t_k, respectively; $\Phi_{k+i, k}$ is the state vector coefficient matrix; $\Psi_{k+i, k}$ is the control vector coefficient matrix; U_k is the control vector; $\Gamma_{k+i, k}$ is the coefficient matrix of the dynamic noise vector; Ω_k is the dynamic noise vector; Δ_{k+i} is the observation noise vector. If we considerate the system has deterministic input, the state equation and observation equation are

$$\begin{cases} X_{k+1} = \Phi_{k+1,k} X_k + \Gamma_{k+1,k} \Omega_k \\ L_{k+1} = B_{k+1} X_{k+1} + \Delta_{k+1} \end{cases} \tag{2}$$

Suppose $\{\Omega_k\}$ and Δ_k are normal sequence and X_0 is a normal vector. And we define n-step forecast residuals as

$$V_{k+i} = L_{k+i} - \hat{L}_{k+i,k} \tag{3}$$

Where: L_{k+i} and $\hat{L}_{k+i,k}$ are the observation values of period $k+i$ and its best prediction value respectively. But

$$\hat{L}_{k+i,k} = B_{k+i} \Phi_{k+i/k} X_k + \Delta_{k+i} \tag{4}$$

Then the variance matrix of V_{k+i} is

$$D_{vv} = B_{k+i} \Phi_{k+i/k} X_k + D_{\Delta_{k+i} \Delta_{k+i}} \sum_{r}^{k+i} B_{k+i} \Phi_{k+i,r} \Gamma_{r,r-1} D_{\Omega_{r-1} \Omega_{r-1}} \Gamma_{r,r-1}^{\mathrm{T}} \Phi_{k+i,r}^{\mathrm{T}} B_{k+i}^{\mathrm{T}} \tag{5}$$

Remember

$$B_{k+i}\varPhi_{k+i,r}\varGamma_{r,r-1} = A^{(k+i,r)} = \left[a_{hi}^{(k+i,r)}\right] \tag{6}$$

Where: $r = 1, \cdots, N$; $k = 1, \cdots, n$; The superscript $k+i,r$ indicates that it is related to k+i,r. It is assumed that $D_{\Omega_{l-1}\Omega_{l-1}}$ is a constant diagonal matrix over the observation period $t_{k+1}, t_{k+1}, \cdots, t_{k+n}$, and it is noted that

$$\mathrm{diag}D_{\Omega\Omega} = \left(\sigma_{11}^2, \ \sigma_{22}^2, \ \cdots, \ \sigma_{rr}^2\right) \tag{7}$$

according to

$$E\left(V_{k+1}^{\mathrm{T}} \cdot V_{k+1}\right) = \mathrm{tr}\left[E\left(V_{k+1}^{\mathrm{T}} \cdot V_{k+1}\right)\right] = \mathrm{tr}D_{vv} \tag{8}$$

Remember

$$\left(V_{k+1}^{\mathrm{T}} \cdot V_{k+1}\right) = D_{vv} + \eta_{k+i} \tag{9}$$

Where: η_{k+i} is the zero mean random variable , $i = 1, 2, \cdots, N$.
Order

$$E_{k+i} = V_{k+i}^{\mathrm{T}}V_{k+i}\,\mathrm{tr}\left[B_{k+i}\varPhi_{k+i,k}D_{X_k}\varPhi_{k+i,k}^{\mathrm{T}}B_{k+i}^{\mathrm{T}}\right] - \mathrm{tr}D_{\Delta_{k+i}\Delta_{k+i}} \tag{10}$$

Remember again

$$\eta = \left[\eta_{k+1}, \cdots, \eta_{k+n}\right]^{\mathrm{T}} \tag{11}$$

Then the wired equations are

$$E = A\mathrm{diag}D_{\Omega\Omega} \tag{12}$$

When $N \geq r$, the above formula has a unique solution. The least square estimation (Least Square,LS) of $\mathrm{diag}D_{\Omega\Omega}$ is

$$\mathrm{diag}D_{\Omega\Omega} = \left(A^{\mathrm{T}}A\right)^{-1}A^{\mathrm{T}}E \tag{13}$$

In this paper, we use the Atheros 9380 network card to obtain CSI information, which can be tested in 20MHz and 40MHz bandwidth, in 20MHz bandwidth, the number of subcarriers is 56, under the bandwidth of 40MHz, there are 114 subcarriers[13], 2 transmitting antennas, 3 receiving antennas, and 6 links in total, in that way, each CSI signal is a complex matrix, where is the number of subcarriers[14].
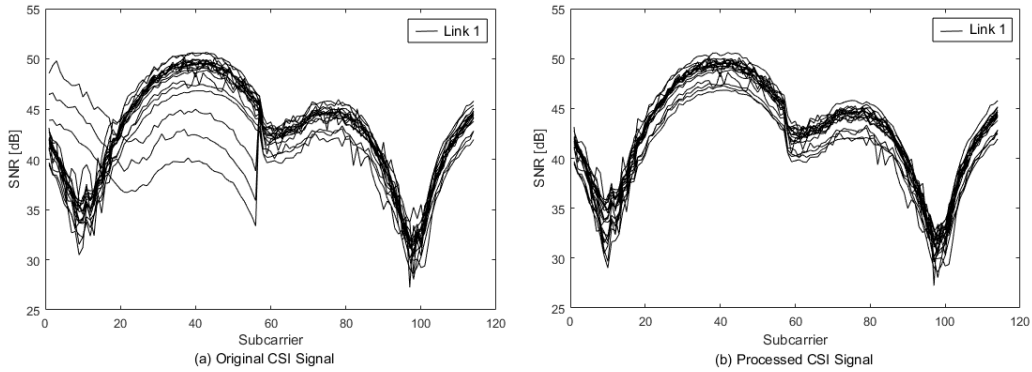

Figure 2. Comparison of original data before and after filtering

As shown in Figure 2, a person stands at a reference point in a static environment, sampled 20 times continuously at different times in 40MHz bandwidth, and filterd the CSI amplitude value of

one link. It could be seen that the adaptive Kalman filtering algorithm is used to reduce the noise of the signal data collected from the original channel, which can reduce the abnormal value to a certain range, get a group of completely processed data the high-quality data and store it in the original database, which provides support for the next step of data classification.

2.3 Binary K-means clustering algorithm

1) Establishment of original collection information database

Assuming that it can collect CSI values of APS at any reference point (x_m, y_m), then the n-th acquisition point can be expressed as:

$$R_i = (R_{i1}, R_{i2}, R_{i3} \cdots R_{in}) i = 1, 2, 3 \cdots m \tag{14}$$

In the statement, R_{in} is the CSI signal vector of the n-th AP node collected by the i-th reference point. If the coordinate of the reference point and its CSI signal vector are combined linearly, it can be expressed as:

$$M_i = (R_{i1}, R_{i2}, R_{i3} ... R_{in}, x_i, y_i) \tag{15}$$

After processing the data of N reference points by the filtering algorithm in Section 2.2, we store the combined value of the effective eigenvectors in the original database in the data structure shown in equation (15) for being called in the clustering operation.

2) Binary k-means algorithm flow

The goal of the standard K-means clustering algorithm is to find the clustering result that minimizes the sum of squares of errors, the initial "cluster center" point is randomly selected by the algorithm. In order to solve this problem, this paper uses an index (SSE) trade-off algorithm which can measure the clustering effect. SSE is the sum of the square of the distance from each sample point to the "cluster center". In addition, the smaller the calculation result is, the closer the data point is to the cluster center, the better the clustering effect is.

The binary K-means algorithm[15] first considers the original database as a sample set to calculate SSE. If the number of clusters is less than $k(k = 2)$ at this time, the minimum value will be divided into two parts for partition operation. Because the algorithm no longer randomly selects the cluster center, but starts from a cluster, the method will not converge to the local minimum value, but to the global minimum value. The specific algorithm flow is as follows:

(1) Initialize the cluster table and combine m sampling points into a cluster.

(2) Take a cluster from the cluster table, set $k = 2$, and use the standard K-means clustering algorithm to cluster the selected cluster.

(3) Select the cluster with the smallest sum of square error from the cluster results and add it to the cluster table.

(4) Judge whether the number of clusters reaches the number of collected reference point data, if it reaches, the clustering ends, otherwise, skip to step (2).

Compared with the standard clustering method, the binary K-means clustering algorithm has better convergence and more stable clustering results[16].

3. Indoor fingerprint location algorithm based on SCI

In the method of fingerprint location, the quality of fingerprint database construction is the main factor that affects the accuracy of location. Therefore, in the off-line stage, this paper combines the relevant theoretical research in Section 2 to establish indoor location fingerprint database.

As the CSI information is obtained by the Atheros 9380 network card, there are 114 subcarriers in the 40MHz bandwidth, so each data packet collected by the reference point is a $m \times n \times 114$ complex matrix H_{MIMO}, where m is the number of transmitting antennas, n is the number of receiving antennas and $v = m \times n$ is the number of antenna pairs.

$$H_{MIMO} = \begin{bmatrix} H_{11} & H_{12} & ... & H_{1n} \\ H_{21} & H_{22} & ... & H_{2n} \\ ... & ... & ... & ... \\ H_{m1} & H_{m2} & ... & H_{mn} \end{bmatrix} \tag{16}$$

Matrix H_{ij} of any antenna pair has 114 complex numbers, and the channel frequency response of each subcarrier is sampled as follows:

$$H_{ij} = \left[h_1, h_2, h_3, ..., h_{114} \right] \tag{17}$$

Among them：$h_i = |h_i| e^{j\sin(\angle h_i)}$

Where: $|h_i|$ is the amplitude and $\angle h_i$ is the phase. Because the phase of CSI can not be accurately extracted due to the influence of frequency offset, we can only extract the amplitude feature as the fingerprint reference. The CSI amplitude is also affected by the multipath propagation of wireless signal in indoor environment[17,18], therefore, in the stage of offline fingerprint database construction, firstly, we process the feature data obtained by variance compensation adaptive Kalman filter, and then train and classify offline the data after noise reduction by clustering algorithm, which will definitely improve the quality of fingerprint database construction in theory. Please see Section 2 for the specific algorithm flow.

In the online location stage, unknown points are extracted to CSI feature information and compared with fingerprint information established in the training stage to estimate the location information of unknown points. The vector coordinates closest to the unknown points and the reference points are calculated by the Euclidean distance, that is, the comparison of any two CSI amplitude vectors i and j Euclidean distance.

$$dis_{i,j} = norm(H_{train\_i} - H_{test\_j}) \tag{18}$$

For V antenna pairs:

$$DIS = \left[Dis_1, Dis_2, ..., Dis_v \right] \tag{19}$$

Because Euclidean distance reflects the "uncorrelation" between space vectors, that is, the smaller the value, the higher the correlation. Therefore, focus on the smaller value of distance, see it as a basis for similarity comparison between test points and training points, and select the first T smaller distances to average as the distance between test points and training points[19].

$$DIS\_mean = \frac{\sum_{i=1}^{T} DIS_{s\_j}}{T} \tag{20}$$

After obtaining the distance between test points and all training points, we use the KNN algorithm as fingerprint matching algorithm to select a position with the smallest distance for estimating the position.

4. Experimental environment deployment and result analysis

4.1 Experimental scene

In this paper, we use the scheme of Atheros 9380 network card to obtain the CSI feature information. All equipments we need for the location algorithm are: Two desktop computers with atheros9380 network card, Intel Core i3-4150 CPU model and Ubuntu 10.04 operating system, in which one machine equipped with two antennas is used as signal transmitters and three antennas of the other with three antennas as receivers, constitute six data links, and carry out the experiment in 40MHz bandwidth.

We selecte laboratory and conference room as our experimental sites to verify the positioning method proposed in this paper: the laboratory site is 9m long and 6m wide, and its plan and real picture are shown in Figure 3 (a) and Figure 3 (b), respectively. The antenna height is set to 0.8m to test it; the conference room is 12m long and 6m wide, and its plan and real picture are shown in Figure 3(c) and Figure 3 (d), respectively, because of the height of the table and chair is 0.8 ~ 1m in the meeting room , the height of the transmitting antenna is 1m, and the height of the receiving antenna is 1.2m.

(a)Meeting room plan

(b) Real view of conference room

(c)Meeting room plan
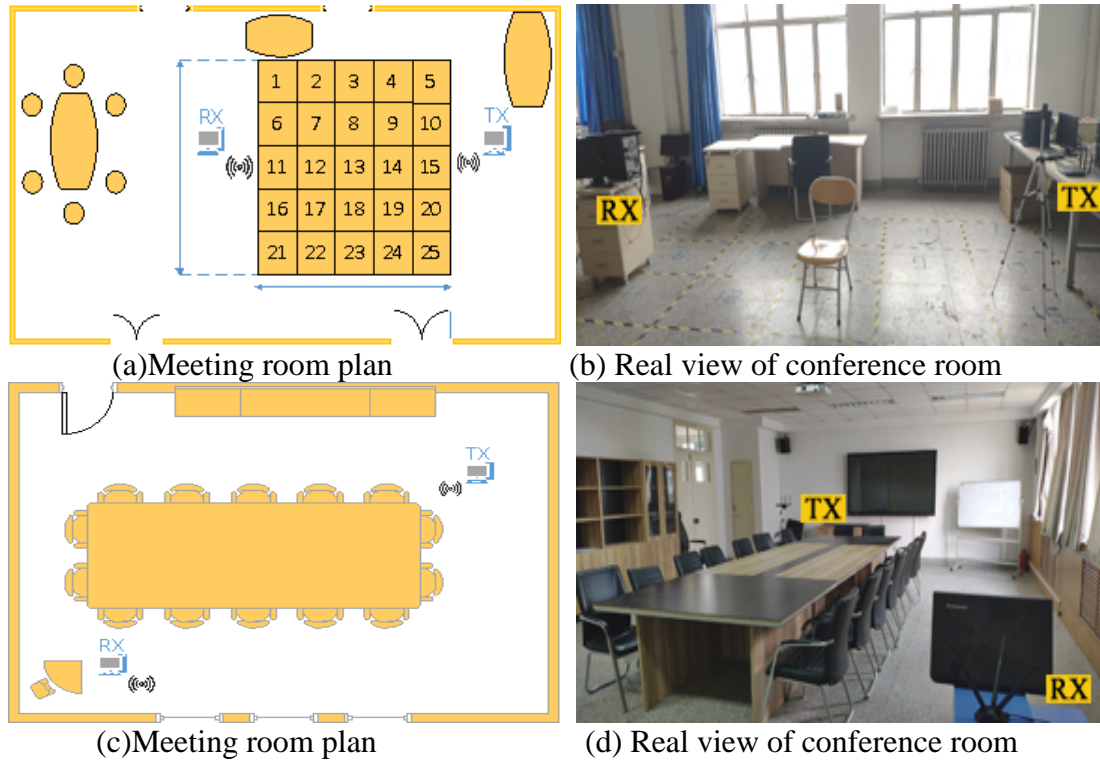
(d) Real view of conference room

Figure 3. Deployment of experimental environment

In the whole test process, the laboratory is named as static scene because the laboratory personnel move less and are relatively static, while the conference room is named as dynamic scene due to a large number of tables, chairs and people's walking behavior.

4.2 Experimental analysis

In order to verify the positioning accuracy and effect of this method in different experimental environments, the evaluation standard measures and analyzes the accuracy and average error[20].

4.2.1 The influence of fingerprint acquisition features on location accuracy

During the experiment, we let an experimenter stand still in the experimental environment shown in Figure 3 and we collected test data at different test points.   Since we can read the RSSI signal features from the CSI data package itself, we adopted the amplitude processed in this paper, the unprocessed and the original RSSI feature data as the fingerprint feature location in the test comparison. The cumulative distribution function of location difference achieved in static and dynamic environments is shown in Figure 4.

From the figure, it can be seen that the overall performance of CSI positioning in both experimental scenarios is better than that of RSSI positioning. The CSI amplitude characteristics processed by this method can achieve positioning accuracy of 0.5-1.5m in static environment, 1-2m in dynamic complex environment, The static environment can reduce the positioning error of 68.2% of the test points to within 1 m, and the dynamic environment can reduce the positioning error of 57.8% of the test points to within 1.5 m. compared with the unprocessed data positioning method, the average positioning accuracy increased by 43.2%, which greatly improved the indoor environment positioning accuracy,and verified the positioning accuracy rate of the amplitude

information processing method in this paper for the static and dynamic complex environment has improved.
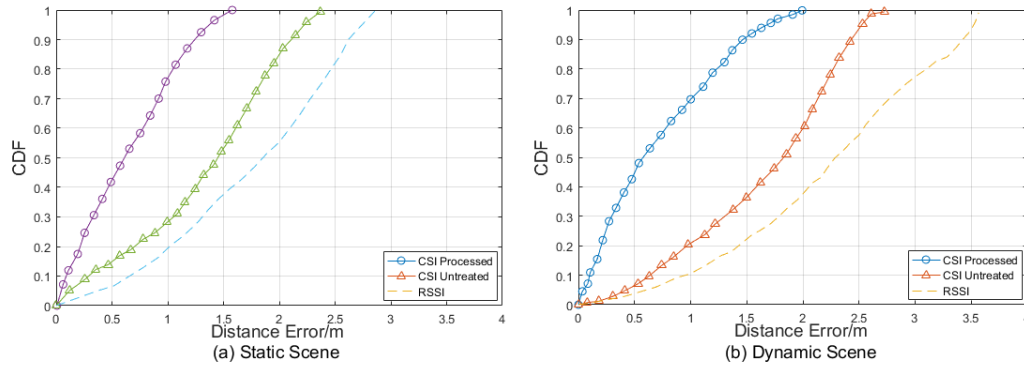

Figure 4. Effect of different feature data on positioning accuracy

4.2.2 Influence of other parameters on positioning accuracy

Because the performance of fingerprint matching algorithm is closely related to the training and test data, the experiment analyzed the influence of different training sample number / test sample number combination on the positioning accuracy, and selected 25, 50, 75 and 100 reference points as parameters respectively, and took the average positioning error as the evaluation index to analyze the algorithm. The influence of different training sample number / test sample number combination and reference point selection on positioning accuracy in static environment is shown in Table 1.

Table 1 Impact of data samples and reference points on positioning accuracy

Reference point	Number of training samples	Number of test samples	Average error/m
25	1000	200	1.575
50	500	200	0.732
75	250	100	1.125
100	100	50	1.725

From the experimental results, it can be seen that when the number of reference points is 50-75, the average positioning error is about 0.7m, which meets the positioning requirements, and the positioning accuracy is relatively high.On the contrary, when the number of reference points is less than 50 or more than 75, the positioning result is relatively poor. The main reason is that when there are too few or too many reference points, the signal multipath effect makes the calculation of the matching algorithm more distorted.

4.2.3 Performance analysis of different location algorithms

According to the experimental results in the previous section, we selected 50 reference points, took 500 / 200 of the test sample data, and used 2 APS to establish the fingerprint database. In the same test scenario, we respectively compared the method proposed in this paper with three algorithms: RSSI based fingerprint location system [4], CSI based FIFs fingerprint location system [5], csi-mimo fingerprint location system [6], The probability cumulative distribution of location distance error in static and dynamic scenarios is shown in Figure 5.

From the experimental results, it shows that the RSSI based positioning method based on the RSSI is vulnerable to the interference of the environment, very unstable, with the largest error. In the dynamic scene, 80% of the average distance error is about 3m. The location method proposed in this paper is based on FIFS and CSI-MIMO. After filtering and clustering, the fingerprint feature is enhanced, and the positioning accuracy is further improved. In the dynamic scene, 90% of the average distance error is within 2 m, 54.4% is within 1 m. In the static scene, 90% of the average distance error is within 1.5m, 72.3% is within 1m, while the positioning accuracy of CSI-MIMO, FIFS and RRSI within 1m is 46.3%, 32.6% and 18.7%, respectively. The main reason for the low positioning accuracy of CSI-MIMO and FIFS is that the original data has not been further analyzed
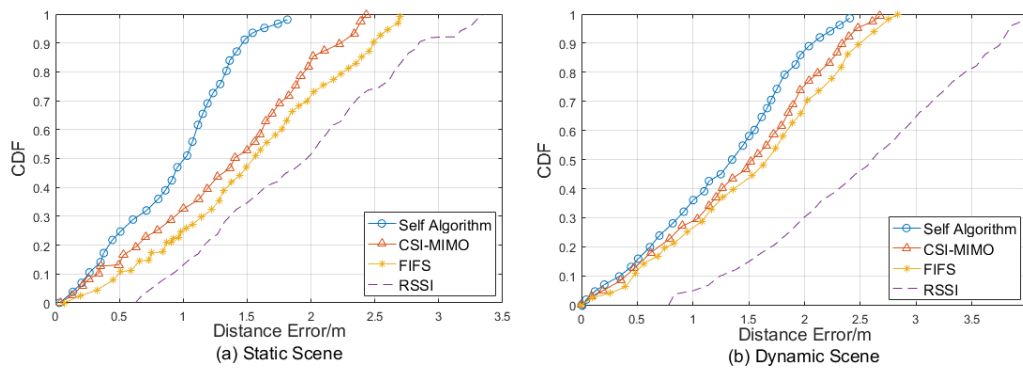
and processed.

Figure 5. CDF of location distance error in two scenarios

5. Conclusion

In this paper, the algorithm is tested and verified in static and dynamic indoor environments. After denoising the original collected feature data by variance compensated adaptive Kalman filter in the offline stage, the multiple feature vectors generated by binary K-means clustering algorithm reduce the impact of indoor multipath effect to a certain extent, so that it has better spatial characteristics, and thus improve the positioning accuracy. Compared with the existing methods and the traditional indoor positioning methods, it is improved. In the following research, we will optimize the complexity of the algorithm.

Acknowledgments

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