Research on Indoor and Outdoor Seamless Positioning Based on Combination of Clustering and GPS

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Abstract. Aiming at the key technical issue which is needed to be solved in seamless positioning, a seamless positioning algorithm based on combination of indoor joint clustering positioning and GPS is proposed in this paper. This algorithm uses GPS satellite positioning technology in outdoor environment and indoor joint clustering positioning algorithm in indoor environment, a switching algorithm is proposed to improve the smoothness of switching when it transit from indoor environment to outdoor one (and vice versa). The experimental results show that the proposed algorithm can meet the requirements of seamless positioning both indoors and outdoors better.

Keywords: Clustering · Gaussian mixture model · Seamless positioning · GPS

1 Introduction

With the development of science and technology, the market of location-based services is growing gradually, and the need of improving the positioning precision and reducing the deployment cost of positioning systems is also increasing. Global positioning system (GPS) dominates the future development of location-based services [1]. GPS positioning system has been relatively well done in outdoor positioning technology. In the outdoor environment, the GPS positioning system has been widely used for its features of high positioning accuracy and wide coverage. However, the signal is vulnerable to the influence of propagation factors such as multipath and obstacles, and the GPS positioning system cannot achieve idea positioning result in the complex urban and indoor environment

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[2–4]. In indoor positioning technology, infrared, Bluetooth, ultrasound, RFID, WLAN and UWB are often used [5–8]. Literature [9] proposed the indoor positioning scheme that integrates Bluetooth and pedestrian track estimation. This method eliminates the instability of Bluetooth system, but the positioning accuracy needs to be further improved. Literature [10] integrated UWB and inertial measurement unit sensor positioning system by Extended Kalman Filter (EKF) which has better performance on correcting the positioning error, but the error accumulation still exists. Aiming at the deficiency of KNN positioning algorithm in indoor positioning, literature [11] proposed an indoor positioning algorithm based on fuzzy set theory, this algorithm is simple and has more precise positioning accuracy. Literature [12] proposed an indoor positioning algorithm based on geometric and RSS clustering, which has the advantages of fast positioning speed and high positioning accuracy, but the training workload is large. By using Bayesian theory, the study [13] proposed a positioning method based on Received Signal Strength Indication (RSSI), which has a better positioning accuracy. Literature [14] proposed a Fingerprint recognition scheme based on Crowdsourcing and multi-source Fusion based Fingerprint Sensing (CMFS). In order to further improve the positioning accuracy of CMFS, ekf-based Fusion algorithm was adopted to fuse the positioning information between Fingerprint and PDR. Literature [15] has developed a wireless performance evaluation platform LAN (WLAN) positioning system based on fingerprint. In the proposed test bed, several scenes are set to test the indoor and outdoor positioning systems.

However, the positioning range of indoor positioning technology is limited. In order to achieve the smooth transition of indoor and outdoor positioning, accurate seamless indoor and outdoor positioning technology is needed in many cases. In 2011, Naohiko and Shusuke had developed a new type of positioning System, the System used the GPS chipset receiver to realize the Indoor positioning, any equipment of GPS receiver chipsets can be detected Indoor Messaging System (IMES) signals for positioning, assisted GPS/IMES developed network, and on the GPS chip firmware to modify the SET, can according to the movement of the user, smoothly to provide location information of seamless Indoor and outdoor [16]. In [17], a low-power iBeacon technology is proposed to run IO detection and location-based services (LBS) on mobile devices. GPS signal is used to trigger off GPS and turn on bluetooth to enable GPS in outdoor environment, while the iBeacon mode of BlueDetect is enabled in semi-outdoor environment to provide LBS. By comparing the signals of two Bluetooth Low Energy (BLE) beacons on both sides of the building entrance, the seamless connection between semi-outdoor environment and indoor environment is realized. In [18], a switching technique for precise monitoring of SNR changes of GPS satellites is proposed. By selecting the high-altitude satellite behind the user and switching it precisely at the entrance, the energy consumption of the algorithm is low. In [19], a universal seamless localization method combining GNSS pseudo-distance and WLAN received signal strength index (RSSI) based on particle filter was proposed. Gaussian process was used to model the spatial RSSI distribution, and these models were used to predict the RSSI of particle positions, and the point estimation of the RSSI likelihood function was obtained. The results of extended kalman filter are compared with pseudo distance and WLAN position. The algorithm achieves precise and robust seamless positioning. In [20], a modular system is proposed, which currently consists of three positioning modules: GPS, gsm-based positioning system and wifi positioning system. The optimal positioning module is automatically selected based on available radio signals, which can provide seamless positioning in different environments. Wu and Geng et al. combined the differential global positioning system (DGPS) with ultra-wideband (UWB), eliminated the UWB non-line-of-sight error (NLOS) with Kalrnan filter, used particle filter for data fusion of different sensors, and used GPRS communication module for wireless data transmission. The system improves the overall positioning accuracy, which can not only meet the indoor and outdoor seamless positioning, but also has a high positioning accuracy [21]. Cai et al. realized seamless indoor and outdoor positioning and navigation by combining GNSS positioning technology and the combination method of indoor geomagnetic fingerprint nodes to solve the problems such as low precision of indoor and outdoor seamless positioning in the transition point and the inability of smooth automatic switching. Since the indoor geomagnetic positioning accuracy is gradually better than GNSS positioning accuracy from outdoor to indoor, the optimal GDOP conversion range value is obtained through analysis and calculation at two critical points of positioning accuracy for smooth switching. Compared with the positioning accuracy of single GNSS or geomagnetic method, the positioning accuracy is improved [22]. In order to solve the problem of discontinuous positioning and low accuracy of current pedestrian navigation in indoor and outdoor environment, Wang and Guo et al. proposed a pedestrian seamless navigation and positioning method based on beidou/GPS/IMU. When the satellite is unlocked, according to the characteristics of the periodicity of pedestrian walking, a zero-speed detection algorithm with multiple conditions and constraints is designed based on IMU. The extended kalman filter can reduce the divergence of inertial sensor with time, and the positioning accuracy of outdoor pedestrian can reach cm [23]. Hu, Liao et al. proposed the indoor and outdoor seamless positioning algorithm gps-lf based on GPS satellite positioning technology and wifi location fingerprint positioning technology. The gps-lf algorithm USES GPS satellite positioning technology for positioning in the outdoor environment. After entering the room, it switches to the wifi location for fingerprint positioning. Multiple groups of wi-fi signal strength values received by the node to be positioned are matched with the location fingerprint database that has been downloaded to the node in advance to estimate the location of the unknown node [24]. In [25], the smart phone is used as the platform to study the indoor and outdoor seamless positioning technology integrating beidou satellite navigation system, wifi, bluetooth and other technologies, and to design the location service application scheme, providing a new idea for the indoor and outdoor seamless positioning. In [26], an intelligent switching algorithm based on counting and threshold mechanism is proposed, which avoids the calculation waste caused by repeated switching of positioning system, reduces the energy consumption of smart phones, and realizes the seamless connection between GPS and indoor wifi location fingerprint positioning technology. In [27], an indoor and outdoor positioning technology and automatic switching strategy of positioning method are designed to provide continuous positioning services. The alpha-count method was introduced to improve the smoothness and reliability of positioning switch. A prototype indoor and outdoor seamless positioning system UL mobile was built, which integrated GPS and wifi.

In this paper, indoor combined clustering and GPS combined positioning method is adopted, Kalman filtering and clustering combined positioning method is adopted indoors, and GPS positioning is used in outdoor environment. In order to reduce the ping-pong effect, a new algorithm named double threshold switching is proposed. Compared with the traditional NN algorithm and K-means-WKNN algorithm, the clustering joint positioning algorithm in this paper has reduced the average positioning error and achieved the seamless switch positioning between indoor and outdoor positioning effectively.

2 Methodology

2.1 Outdoor Positioning Principle

GPS positioning system is composed of 24 to 32 satellites or space crafts, and the system consists of the space section, ground control section and users [28]. The space section of GPS is composed of 24 working satellites, providing the navigation system with continuous global navigation capability in time. The observation, collection and tracking data of the ground control part can be conducted according to the positioning calculation method after the tracking satellite signal is captured by the user. The principle of GPS positioning is shown in Fig. 1.

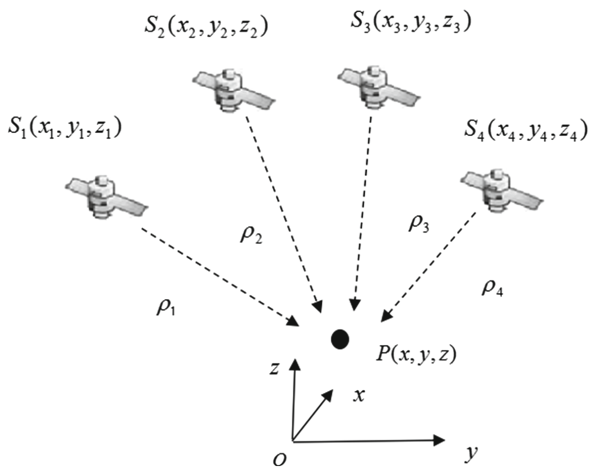

Fig. 1. GPS positioning

P is the position to be measured, the distance from P to four satellites measured by GPS receiver is $\rho_1, \rho_2, \rho_3, \rho_4$ respectively, and the observation equation to solve the position of P is:

$$\begin{cases} \rho_1^2 = (x - x_1)^2 + (y - y_1)^2 + (z - z_1)^2 + c\delta_t \\ \rho_2^2 = (x - x_2)^2 + (y - y_2)^2 + (z - z_2)^2 + c\delta_t \\ \rho_3^2 = (x - x_3)^2 + (y - y_3)^2 + (z - z_3)^2 + c\delta_t \\ \rho_4^2 = (x - x_4)^2 + (y - y_4)^2 + (z - z_4)^2 + c\delta_t \end{cases} \tag{1}$$

Where c is the speed of light and δ_t is the clock difference of the receiver. Due to various types of errors, in order to achieve the positioning accuracy, at least four satellites are needed to be observed simultaneously to achieve the positioning.

2.2 Indoor Positioning Principle

In this algorithm, fingerprint database is established in the offline phase. K-means clustering algorithm and GMM clustering algorithm are used to get the clustering fingerprint database. The Euclidean distance between the test signal and each clustering center is calculated, and the test point is classified into the class with the smallest Euclidean distance value until all test points are classified. The Euclidean distance between the test signal and the clustering fingerprint database was calculated, K positions with the smallest Euclidean distance were selected, the weight was calculated, and the position coordinates were estimated according to the weight. Kalman filter is applied to the estimated position and the positioning result is optimized to obtain the position of the point to be measured. The positioning process is shown in Fig. 2.

K-Means Clustering Algorithm. The K-means clustering algorithm assumes the set X $\sim \{x_1, x_2, \ldots, x_n\}$ that contains N data (objects), and divides this data set into K clustering center sets C $\sim \{c_1, c_2, \ldots, c_K\}$ [29]. If the sample number of class i is N_i, then $N = \sum_{i=1}^{K} N_i$, and the mean value of each class C_i is $\{m_1, m_2, \ldots, m_K\}$, then $m_i = \frac{1}{N} \sum_{n=1}^{N_i} x_n$, i = 1, 2 ... , K. The minimum objective function of K-means clustering algorithm is:

$$J = \sum_{i=1}^{K} \sum_{n=1}^{N_i} \|x_n - m_i\|^2 \tag{2}$$

Gaussian Mixture Model Algorithm (GMM). Gaussian mixture model positioning method can be regarded as a fingerprint probability method. Suppose the entire data set is generated by k Gaussian models, then the model parameters and which Gaussian model is most likely to generate each data point are calculated by EM algorithm, and finally the data points generated by the same Gaussian model are divided into one class. Gaussian mixture model refers

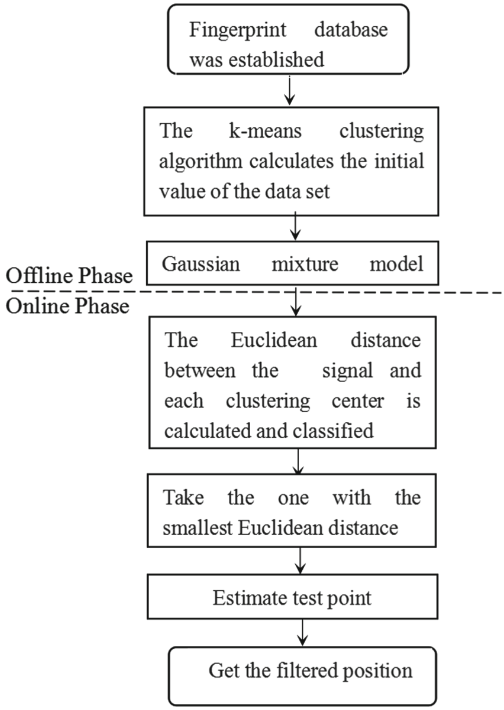

Fig. 2. Position flow chart

to the probability distribution model with the following forms:

$$P(x \mid \theta) = \sum_{i=1}^{K} \alpha_i \phi (x \mid \theta_i) \tag{3}$$

In Eq. 3, α_i is the coefficient, $\alpha_i \geq 0$, $\sum_{i=1}^{K} \alpha_i = 1$; X is the observation data, x $= \{x_1, x_2, \ldots, x_n\}$, $\phi(x \mid \theta_i)$ is the Gaussian distribution density function, $\theta_i = (\mu_i, \sigma_i^2)$,

$$\phi(x \mid \theta_i) = \frac{1}{\sqrt{2\pi}\sigma_i} \exp\left(-\frac{(x-\mu_i)^2}{2\sigma_i^2}\right) \tag{4}$$

It's called the ith submodel.

Expectation maximization (EM) algorithm is adopted for the estimation of model parameters [30]. The EM algorithm includes two steps: the expected step (e-step) and the maximum stride length (m-step).In the first iteration, the parameters are initialized, the covariance matrix is set to the identity matrix,The ith gaussian weight coefficient is $\alpha_i = \frac{1}{K}$, the parameter $\hat{\theta}$ that maximizes the logarithmic likelihood function of x is obtained.

$$\hat{\theta} = \arg\ max_{\theta} p(x \mid \theta) \tag{5}$$

Step E finds the expected value of the hidden variable from the current parameter and the estimated variable $\hat{\gamma}_{ji}$, $j = 1, 2, \cdots, n$, $i = 1, 2, \cdots, K$.

$$\hat{\gamma}_{ji} = \frac{\alpha_i \phi (x_j \mid \theta_i)}{\sum_{i=1}^{K} \alpha_i \phi (x_j \mid \theta_i)} \tag{6}$$

Step M to obtain the maximum expected logarithmic likelihood function of the observed data.

$$\hat{\mu} = \frac{\sum_{j=1}^{n} \hat{\gamma}_{ji} y_j}{\sum_{j=1}^{n} \hat{\gamma}_{ji}} \tag{7}$$

$$\hat{\sigma}^2 = \frac{\sum_{j=1}^{n} \hat{\gamma}_{ji} (y_j - \mu_i)^2}{\sum_{j=1}^{n} \hat{\gamma}_{ji}} \tag{8}$$

$$\hat{\alpha}_i = \frac{\sum_{j=1}^{n} \hat{\gamma}_{ji}}{n} \tag{9}$$

Repeat these two steps until the change of the mean value of two successive iterations is lower than the threshold value which has been set, and finally obtain the parameter to be estimated.

The Establishment of Signal Fingerprint Database. Multiple WiFi signals can be collected at a certain location in the positioning area, and multiple WiFi signals collected at the same location constitute the feature vector of the signal (RSS). Assuming that there are M WiFi hotspots in the location scene and WiFi signals are collected for N times,the sample data set can be expressed as $I = \{x_i, y_i, f_i\}$, Where $i = 1, 2, \cdots, N$, $f_i = (f_{i1}, f_{i2}, \cdots, f_{iM})$, (x_i, y_i) represents the corresponding position of the vector f_i. The process of fingerprint positioning is shown in Fig. 3.

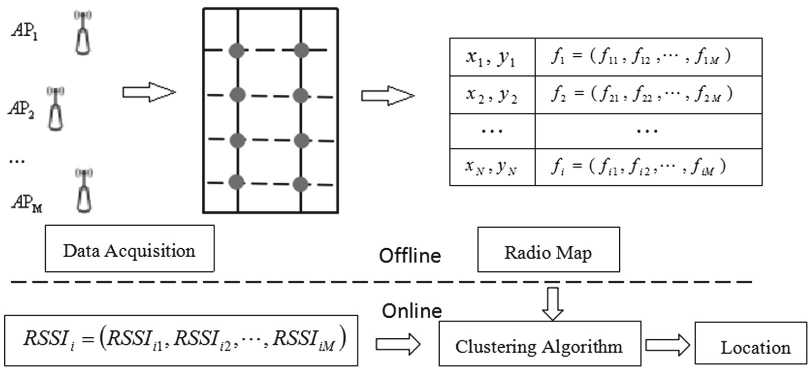

Fig. 3. Fingerprint locating process

In the off-line phase, in order to obtain the global optimal solution, the number of sub-models is first determined, and the above k-means algorithm is used to calculate the initial value of the constructed sample data set model. Then, GMM clustering is used to obtain the fingerprint database S after clustering.

$$S = \{s_1, s_2, \cdots, s_j\} \tag{10}$$

The center of clustering $C_j = \{c_{j1}, c_{j2}, \cdots, c_{jM}\}$, Where j is the number of classes.

Online Positioning Stage. $RSSI_i = (RSSI_{i1}, RSSI_{i2}, \cdots, RSSI_{iM})$ is the collected test signal, $i = 1, 2 \cdots, n$, n is the number of test points. The Euclidean distance D of each test signal $RSSI_i$ and the clustering center value C_j can be expressed as

$$D_{ij} = \sqrt{\sum_{N=1}^{M} (RSSI_{iN} - c_{jN})^2} \tag{11}$$

In this formula, $i = 1, 2 \cdots, n$, j is the number of clustering.

The size of Euclidean distance between each test signal and each cluster center value was compared, and the clustering with the smallest Euclidean distance was selected to classify the test points into the cluster until all the test points were classified.

The Euclidean distance O between the measured signal and the cluster fingerprint database is calculated, K positions with the smallest Euclidean distance are selected, and the weight w_i is calculated, $i = 1, 2 \cdots, K$.

$$w_i = \frac{O_i}{\sum_{i=1}^{K} O_i} \tag{12}$$

The position coordinates are estimated according to the weight values obtained, as follows:

$$\hat{x} = \sum_{i=1}^{K} w_i x_i, \hat{y} = \sum_{i=1}^{K} w_i y_i \tag{13}$$

In this paper, the joint clustering algorithm is used to calculate the location of the measured points, and then Kalman filtering algorithm is used to filter the estimated position coordinates. The position coordinates after Kalman filtering are relatively close to the real coordinates.

2.3 Clustering and GPS Combined Positioning Algorithm

In order to ensure the continuity of positioning service, the positioning method in the positioning area is an important factor to be considered in the positioning process. The seamless positioning scheme in this paper is as follows:

Step 1: when WiFi signal is available and GPS signal cannot be detected, indoor clustering joint positioning algorithm is adopted.
Step 2: when there is WiFi signal and the number of GPS satellites is less than 4, clustering and GPS combined positioning algorithm are adopted.

Step 3: when the number of GPS satellites is greater than or equal to 4, GPS positioning is adopted.

The specific implementation of combined positioning is as follows:
(1) Mean positioning error can be expressed as:

$$E = \sqrt{(\hat{x} - x)^2 + (\hat{y} - y)^2} \tag{14}$$

$(\hat{x}, \hat{y})$ is the estimated position coordinate of the to be measured point, and (x, y) is the true position coordinate of the point to be measured.

The system parameters T of combined positioning are determined by mean positioning error E and Euclidean distance O, which can be expressed as:

$$T = \alpha E + (1 - \alpha) O \tag{15}$$

α is the weighted factor.

(2) Double threshold value h_1, h_2 is used in this paper, when users go from indoor to outdoor. If T is less than the setting threshold h_1, the indoor clustering joint positioning algorithm is adopted. If T is greater than the setting threshold h_1, then GPS positioning is adopted.

(3) When the user walks into the room from outside, if T is larger than the threshold value h_2, GPS positioning is adopted. If T is less than the threshold value h_2, the indoor clustering joint positioning algorithm is adopted.

The flow chart of combined positioning is shown in Fig. 4.

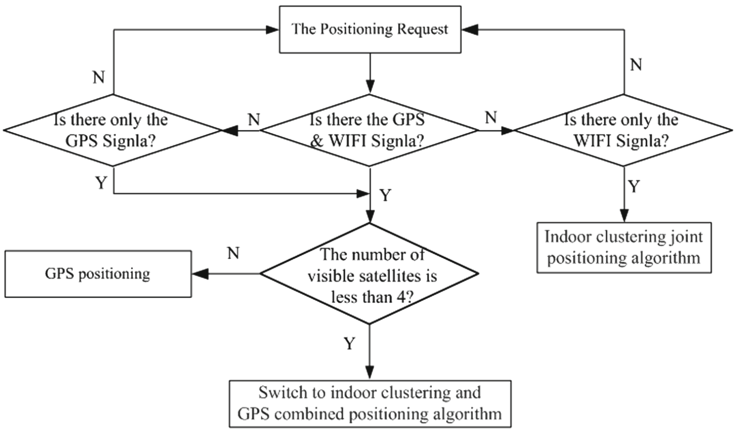

Fig. 4. Combined positioning flow chart

3 Experiments and Analysis

Experiments of indoor cluster joint positioning and combined positioning were carried out based on experimental data. Six AP were arranged in a $20\,\text{m} \times 15\,\text{m}$

Table 1. Cluster number error analysis

Cluster number	3	4	5
Average localization error	1.650	2.820	2.473

Table 2. The number of adjacent points k-value positioning error probability statistics

K	6	7	8	9	10
The error is less than 1 m	18.6	25.7	24.3	33.3	27.1
The error is less than 2 m	72.9	75.7	80.0	78.6	70
The error is less than 3 m	88.6	87.1	90.0	88.6	87.1

room. The RSSI values of 6 wireless access points were sampled at each sampling point. The selected wireless route AP is TP-LINK, and the type number is TL-WR842N, the signal receiver used in the test is samsung Galaxy S7 mobile phone. After reading the signal strength for 50 times, the mean value was taken and the mean value of RSSI was recorded into the fingerprint database. MATLAB software was used to achieve the positioning algorithm, the positioning results and positioning errors of the test points were obtained through experiments.

Table 1 shows the results of the experimental analysis on the value of the number of clusters, and the positioning error results with the number of clusters of 3, 4 and 5 are statistically analyzed. The results show that when the number of clusters is set to 3, the average positioning error is the minimum. Therefore, the number of clusters set in the experiment is 3. Table 2 is the result of experimental analysis on values of adjacent points, and the positioning results of K = 6, 7, 8, 9, 10 are statistically analyzed. As can be seen from the table, when K = 9, the probability of error less than 1 m is 33.3%. Therefore, K value is selected as 9 in this experiment. Figure 5 shows the cumulative probability distribution of distance errors before and after Kalman filtering. It can be seen from the figure that the positioning accuracy within 2 m can be improved from 75% to 80% after Kalman filtering. Figure 6 is the distance error cumulative distribution function of the joint positioning algorithm, K-means-WKNN algorithm and NN algorithm. The positioning accuracy of the joint positioning algorithm within 2 m is 83%, that of the NN algorithm is 69%, that of the K-means-WKNN algorithm is 66%, that of the joint positioning algorithm within 1 m is 41%, and that of the NN algorithm and the K-means-WKNN algorithm is 32%. It can be seen that the positioning performance of the joint positioning algorithm is significantly better than the other two algorithms.

The positioning error results of the three algorithms are shown in Table 3. The experimental results show that the positioning error of the joint localization algorithm is about 1.6 m, while that of the NN algorithm and the K-means-WKNN algorithm is about 2.2 m. The combined positioning algorithm reduces the average positioning error by 17% compared with the NN algorithm, and the average positioning error by 24% compared with the K-means-WKNN algorithm. The

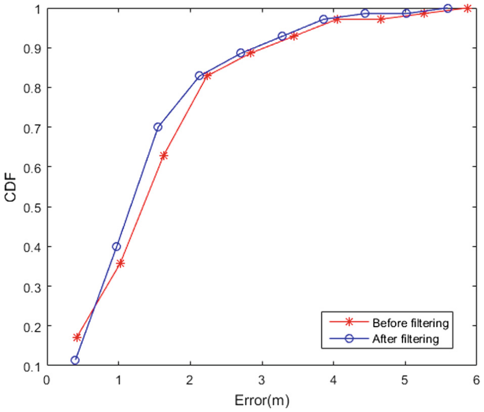

Fig. 5. Comparison before and after Kalman filtering

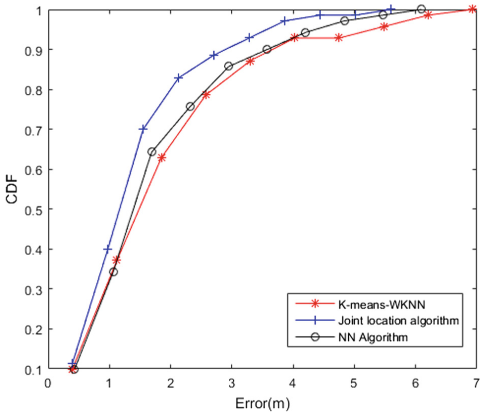

Fig. 6. Cumulative distribution function of distance error

Table 3. Position error results of three algorithms

Algorithm	Mean error	Maximum error	Error minimum
NN algorithm	1.989	6.407	0.119
K-means-WKNN algorithm	2.170	7.289	0.034
Joint location algorithm	1.651	5.879	0.109

error accumulation function converges the fastest, and it has a better positioning effect indoors.

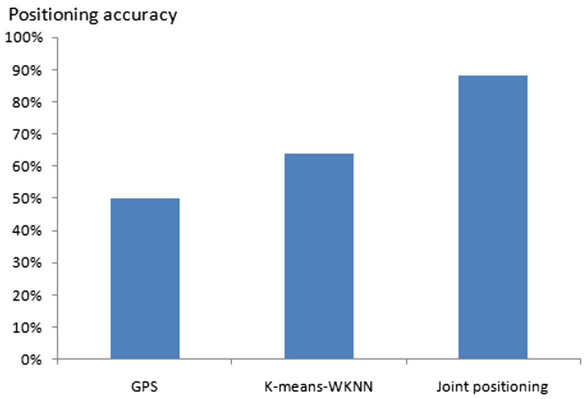

Fig. 7. The precision of the three positioning methods

In the experimental process, 50 points were measured using the clustering joint localization algorithm, K-means-WKNN positioning algorithm and GPS positioning algorithm respectively, and the positioning accuracy of the three positioning methods was obtained as shown in Fig. 7. When the user enters the switching area and reaches the threshold, the switching positioning method is adopted. The plan sketch of the positioning switching area is shown in Fig. 8, and the switching judgment diagram is shown in Fig. 9. Selecting the appropriate threshold can improve the stability of the switching process. The weighted factor $\alpha = 0.6$, the values of h_1 and h_2 re four and six respectively.

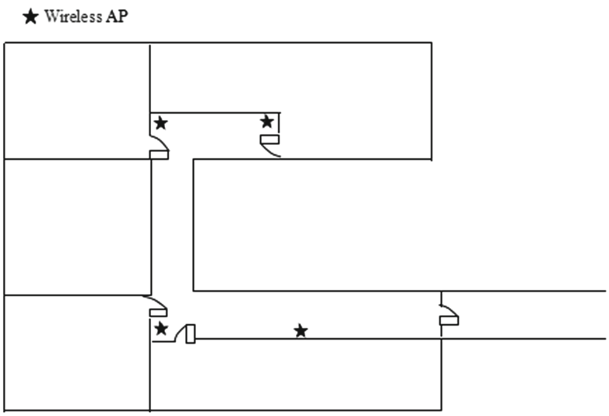

Fig. 8. Plan sketch of positioning switching area and WiFi signal source arrangement

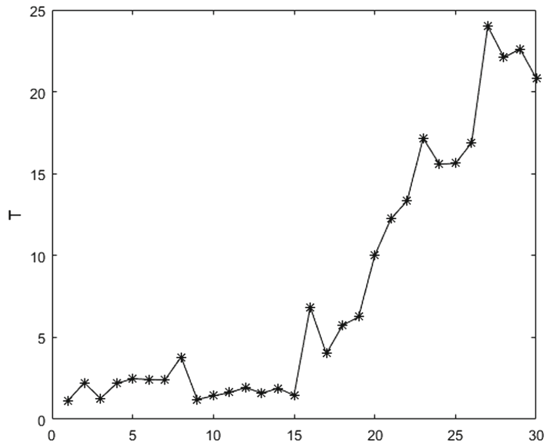

Fig. 9. Switching decision diagram

It can be obtained from the experimental data that GPS positioning cannot achieve high precision positioning indoors. Compared with the K-means-WKNN algorithm, the positioning algorithm proposed in this paper effectively improves the positioning accuracy and realizes seamless positioning indoors and outdoors.

4 Conclusions

The existing single positioning technology cannot meet the needs of the indoor and outdoor positioning at the same time, this paper proposes a method that combines indoor clustering joint positioning with GPS positioning algorithm, the average positioning error in this algorithm is reduced 17% and 24% compared with that of NN algorithm and K-means-WKNN algorithm respectively. This way effectively improves the positioning accuracy and realizes the seamless switching positioning between indoor and outdoor positioning system.

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