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Research on Indoor Visible Light Location Based on Fusion Clustering Algorithm

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Abstract: Aiming at the problem of large positioning errors in the boundary area, a new location fingerprint location method based on a fusion clustering algorithm is proposed. This clustering-based method embodies the idea of rough location first and then fine location. Firstly, the edge regions of the received signal strength (RSS) samples which are greatly affected by reflection are divided using the k-medoids algorithm, and then the center part is clustered via density-based spatial clustering of applications with noise (DBSCAN). In the actual location estimation stage, the points to be measured can only be located in one of the classified areas, and combined with the optimal k-nearest neighbor algorithm (WOKNN) to match the location. The results show that the average positioning error of the algorithm is 13 cm in an indoor environment of 5 m × 5 m × 3 m. Compared with the traditional method without clustering, the positioning accuracy of the edge area is increased by 21%, and the overall improvement is 33.8%, which proves that the proposed algorithm effectively improves the efficiency of real-time positioning and indoor positioning accuracy.

Keywords: indoor localization; visible light positioning; region division; fingerprinting; DBSCAN algorithm

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1. Introduction

With the increasing improvement in the Internet of Things, the application of location-based services has attracted much attention. Large-scale indoor construction is increasing gradually, and the demand for indoor positioning is increasing rapidly. In recent years, indoor positioning has been widely used in urban construction, medical services, construction sites, chemical metallurgy, power plants, and other fields. Especially in the field of architecture, the main applications include emergency management [1], intelligent energy management [2], heating, ventilation, and air conditioning systems (HVAC) controls [3], and occupancy detection [4]; real-time accurate knowledge of the location of people in a building is useful for a variety of applications. At present, indoor wireless positioning technologies are being developed, including wireless local area network (WLAN), radio frequency identification (RFID), Bluetooth, ultra-wideband (UWB), ultrasonic and infrared. Among these technologies, WiFi-based and Bluetooth-based low-energy (BLE) location technologies have developed into the most commonly used methods and are widely deployed in current smart devices, mainly because they do not need the line-of-sight path between the transmitter and the receiver [5]. However, WiFi location relies on the assumption that the signal strength at each point in space does not change with time or other obstacles, which is unrealistic in real-world scenarios, and WiFi location results are often unreliable. Multiple-input multiple-output (MIMO) communication has long played an important role in RF-based communications. By using MIMO, data rates can be increased without any increase in bandwidth or power, increasing channel capacity and effectively supporting multiple users [6].

Different from the above indoor positioning technology based on radio frequency communication, visible light positioning (VLP) technology is based on indoor VLC technology, and indoor positioning can be realized by using LED lamps for lighting. Visible light communication (VLC) has developed rapidly with its advantages of green, anti-electromagnetic interference, and rich spectrum resources. It can be used to enhance future wireless communication systems and has great potential to provide reliable solutions for indoor positioning problems. Sejan studied the VLC technology in the MIMO communication environment and considered the machine learning method for MIMO VLC [7]. In order to construct a VLP system, methods such as angle of arrival (AOA), time of arrival (TOA), and received signal strength (RSS) can be used, while TOA requires strict synchronization of transmission and reception, and AOA requires higher hardware. Therefore, the method based on RSS attracts extensive attention because of its low cost and simple hardware [8]. Previous research based on VLC ignored the reflection of ceilings, walls, and indoor objects, which made the positioning effect too ideal and seriously inconsistent with the results in the actual environment. In 2016, Aminikashani demonstrated the influence of multipath reflection, and the central area of the room was almost unaffected. In contrast, other areas (namely corners and edges) had a very bad effect [9]. It is pointed out that using a clustering algorithm before location, the process of querying the closest point only occurs in one area, which can shorten the total execution time and improve the location accuracy [10]. In 2016, Saadi only used two LEDs and the k-means clustering method and obtained an average localization error of 31 cm, which is the best accuracy achieved in any practical environment using LEDs [11]. At present, k-means is widely used in indoor positioning, but its initial centroid selection is random, which will cause the clustering to fall into the local optimal solution, resulting in poor clustering results. In 2018, Wang Hui studied the visible light positioning system model based on the binary k-means clustering method, which made the clustering effect better and simplified the computational complexity [12]. Dividing by region can guarantee signal integrity in each region, but the fingerprint points in the edge region of the cluster may be divided into the wrong cluster. In 2022, Ren proposed a hybrid localization algorithm based on extreme learning machine (ELM) and DBSCAN to solve the problem of large boundary errors between edges and corner clusters. Through comparison, it was found that the DBSCAN clustering algorithm is the best maximum likelihood localization algorithm [13]. In the same year, Martínez proposed a new VLP system with RGB LEDs for multi-cell networks, which uses Euclidean distance and RGB LED position to estimate the position of the receiver through a trilateration algorithm. This architecture can be extended to multiple units according to the area of application scenarios and has practical application [14]. In order to better realize real-time positioning, in 2023, Long divided the positioning points into ordinary points, edge points, and blind spots, and used corresponding models to deal with different types of points, respectively, which was the first study to consider the different effects of multipath effects in different areas of the room, and realized centimeter-level positioning [15].

Improving the accuracy of indoor visible light positioning systems with a simple, real-time, and robust approach is one of the challenges in recent research [16]. In this paper, we consider a VLC channel model including line-of-sight (LOS) and non-line-of-sight (NLOS) components. On the basis of the k-means algorithm, considering that the randomness of clustering will bring great instability to location, a fusion clustering method of k-medoids combined with DBSCAN is proposed, which has low algorithm complexity and can ensure that fingerprints in the same environment, at different times and at the same location, have high similarity. Then, the fusion clustering algorithm and the WOKNN algorithm are combined to discuss the localization of different regions and verify the robustness and effectiveness of the algorithm.

2. Indoor Model and Algorithm Principle

2.1. System Model

The indoor visible light positioning system based on RSS is mainly composed of an LED light source, a visible light channel, and a PD array, as shown in Figure 1. In this paper, the size of the room is set to 5 m × 5 m × 3 m, and four LED arrays are evenly and symmetrically installed on the ceiling, which are used as emission sources and located at (1, 1, 3), (1, 4, 3), (4, 1, 3), and (4, 4, 3), and the receiving end is placed horizontally upwards at any position on the ground.

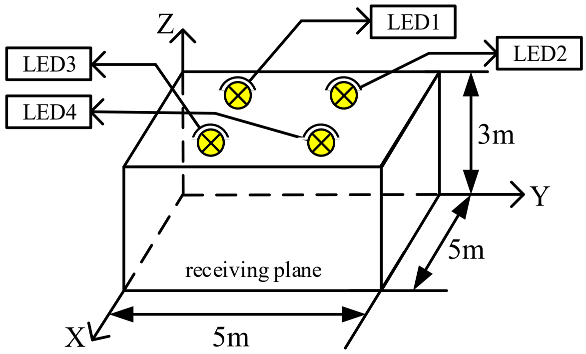


Figure 1. Indoor VLC system model.

2.2. Channel Model

In this study, according to the actual indoor environment, the LOS link and the NLOS link with primary wall reflection are considered. The communication link is shown in Figure 2. Assuming that the luminous intensity of LED obeys the Lambert radiation model, the channel gain in the LOS link can be expressed as [17]:

$$H_{LOS}(0) = \begin{cases} \frac{(m+1)A_r \cos^m(\phi)\cos(\varphi)}{2\pi d^2} T(\varphi)g(\varphi) & 0 \le \varphi \le \varphi_{FOV} \\ 0 & \varphi > \varphi_{FOV} \end{cases} \quad (1)$$

where A_r is the physical area of the photodetector (PD) and m is the Lambert radiation order. d is the distance between LED and PD, φ is the incident angle, ϕ is the irradiance angle, and φ_{FOV} is the field of view (FOV) of the receiver. $T(\varphi)$ and $g(\varphi)$, respectively, represent the gains of the optical filter and optical condenser of the receiver, which can be expressed as [18]:

$$g(\varphi) = \begin{cases} \frac{n^2}{\sin^2(\varphi_{\mathrm{FOV}})} & 0 \le \varphi \le \varphi_{\mathrm{FOV}} \\ 0 & \varphi > \varphi_{\mathrm{FOV}} \end{cases} \quad (2)$$

where n is the refractive index of the optical concentrator.

Assuming that the wall consists of many diffuse mirrors with an area of ΔA and a reflectivity of RW, the channel gain of the first-order reflection is obtained using the following formula.

$$H_{\mathrm{dif}}(0) = \begin{cases} \sum\limits_{\mathrm{Wall}} \frac{A_r \Delta A R_W (m+1)}{2\pi^2 d_1^2 d_2^2} \cos^m(\phi_1)\cos(\varphi_1)\cos(\phi_2)\cos(\varphi_2)T(\varphi_2)g(\varphi_2) & 0 \le \varphi_2 \le \varphi_{\mathrm{FOV}} \\ 0 & \varphi_2 > \varphi_{\mathrm{FOV}} \end{cases} \quad (3)$$

where d_1 and d_2 are distances, φ_1, and φ_2 are incident angles, ϕ_1, and ϕ_2 are irradiance angles, R_W is the reflectivity of the wall, and ΔA is the area element of the reflection point of the wall.

The final total received power is expressed as:

$$P_{rs} = \{RP_t[H_{LOS}(0) + H_{dif}(0)]\}^2 + \sigma_{noise}^2 \quad (4)$$

where P_{rs} is the received power, P_{t} is the transmitted power, R is the responsivity of the receiver, and σ^2_{noise} is the variance of the total noise. Consider that in a typical visible light positioning system, LEDs are modulated to transmit signals, and time division multiplexing (TDM), frequency division multiplexing (FDM), or code division multiplexing (CDM) methods are used to realize multiple access of different LEDs. Therefore, inter-symbol interference can be avoided and background noise can be filtered out. The variance of noise can be expressed as [19]:

$$\begin{aligned}\sigma^2_{\text{noise}} &= \sigma^2_{shot} + \sigma^2_{thermal} \\ &= (2qRP_{\text{rs}}B) + \left(\frac{8\pi kT_{\text{k}}}{G}\eta A_{\text{r}} I_2 B^2 + \frac{16\pi^2 kT_{\text{k}}\Gamma}{g_{\text{m}}}\eta^2 A_{\text{r}}^2 I_3 B^3\right)\end{aligned} \tag{5}$$

where q, B, and k represent charge, equivalent noise bandwidth, and Boltzmann constant, respectively, and k = 1.38 $\times$ 10^{-23}. T_{k}, G, and η represent absolute temperature, open-loop voltage gain, and fixed capacitance of PD, respectively. Γ and g_{m} represent field effect transistor (FET) channel noise figure and FET transconductance, respectively. I_2 and I_3 are 0.562 and 0.0868, respectively.

The signal-to-noise ratio (SNR) is expressed as [20]:

$$\text{SNR} = \frac{\text{P}_r^2}{\sigma^2_{\text{noise}}} = \frac{\{\text{RP}_{\text{t}}[\text{H}_{\text{LOS}}(0) + \text{H}_{\text{dif}}(0)]\}^2}{\sigma^2_{\text{shot}} + \sigma^2_{\text{thermal}}} \tag{6}$$

where P_{r}^2 is the signal power of the receiver.

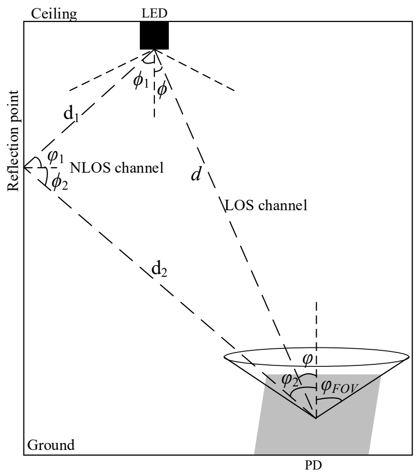


Figure 2. Indoor visible light channel.

2.3. Fingerprint Location Method

The fingerprint method is a location algorithm that infers the final location of the location target through the physical location coordinates and its signal characteristics (such as RSS value) and matching algorithm, which has a better inhibitory effect on multipath effect and non-line-of-sight propagation of signals [21]. It mainly includes offline mode (training) and online mode (testing), as shown in Figure 3.

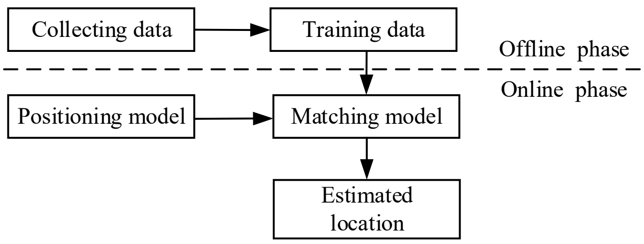


Figure 3. Indoor positioning system based on fingerprint.

The main task of the offline mode is to collect RSS from all fingerprints, and each physical location should have a unique and distinguishable fingerprint, and then noise reduction, regional division, and training are carried out in turn, and a fingerprint database is established according to certain rules [22]. The online mode uses the training data in the offline stage to predict the current position of PD. The existing matching algorithms include nearest neighbor (NN), k nearest neighbor (KNN), weighted k nearest neighbor (WKNN), neural network, and support vector machine (SVM) [23].

3. Improved Fingerprint Method

The research of fingerprint technology is divided into two directions: the establishment of a fingerprint database in the offline stage and the optimization of the matching algorithm in the online stage. In summary, the proposed algorithm is shown in block diagram 4 (Figure 4). Considering the comprehensive characteristics of RSS in the offline stage, a fusion clustering algorithm is proposed. In the online positioning stage, the Euclidean distance between the point to be measured and the RSS value of the central node of each cluster is calculated, and the positioning area is narrowed to the area where the cluster closest to the central node is located, and the coordinate information of the positioning point is estimated using the best matching model to complete the positioning.

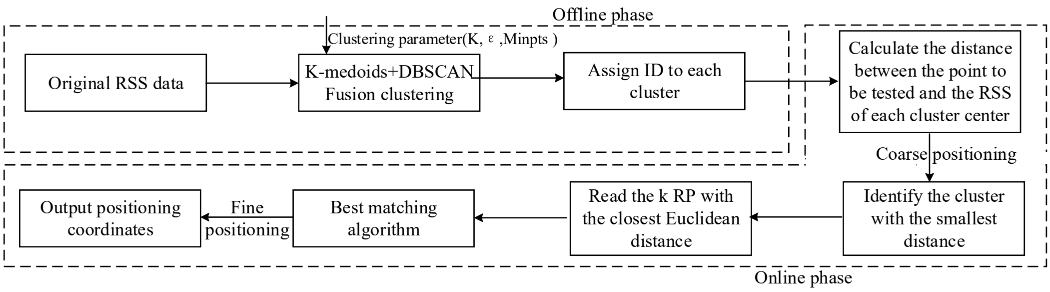


Figure 4. Indoor positioning system based on fingerprint.

3.1. *Offline Phase*

The purpose of offline clustering is to reduce the space and computational complexity of fingerprint search, and the most important thing is to improve the correctness of fingerprint matching and the accuracy of location [24]. The proposed fusion clustering is as follows: the k-medoids algorithm divides the edge and the middle region, and the DBSCAN algorithm distributes the middle part according to the light intensity distribution characteristics. Feature extraction is also very important for NLOS recognition and mitigation. The clustering effect is often measured using DB (Davies–Bouldin), SI (silhouette index), and the sum of squares of error (SSE). The smaller the DB or the larger the SI or the smaller the SSE, the closer the data objects are to their centroids, and the better the clustering effect [25].

3.1.1. K-Medoids Algorithm

The k-medoids algorithm is optimized via k-means. K-means takes the center point as the average of all data points in the current cluster, while in k-medoids, the point with the smallest distance from the current cluster to all other points (in the current cluster) is selected as the central point, which solves the problem of being sensitive to abnormal points and being greatly affected by extreme values.

The algorithm flow chart is shown in Figure 5, and the detailed steps are as follows [26]:

Randomly select k points from the total n sample points as medoids. According to the principle of being closest to medoids, assign the remaining n-k points to the class represented by the current best medoids. For all the other points corresponding to category i class, except the corresponding medoids points, calculate the value of the cost function in order when it is the new medoids, traverse all possible points, and select the point corresponding to the minimum cost function as the new medoids. Repeat the first two processes until all medoid points no longer change or have reached the set maximum number of iterations; the final k is produced.

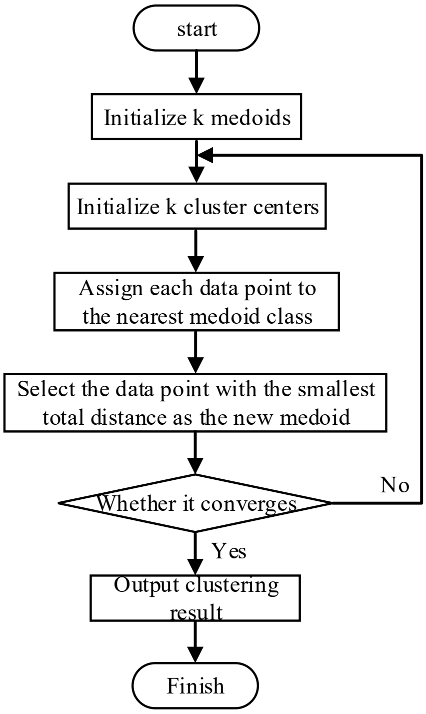


Figure 5. K-medoids clustering algorithm flow chart.

3.1.2. DBSCAN Algorithm

The DBSCAN, proposed by Ester in 1996, is a non-parametric, density-based clustering technology. Its advantage is that it does not need to specify the number of clusters in advance, divides high-density points into clusters, and it can effectively deal with low-density noise points [27]. Using the DBSCAN algorithm, the points of the fingerprint data set into core points, boundary points, and noise points were divided. As shown in Figure 6, the type that each point belongs to depends on sample distribution, Eps, and Minpts. Eps is the radius of the region to determine whether the data points are located in the cluster, and Minpts specifies the minimum number of points needed to form the cluster. The initial selection of Eps and Minpts has a great influence on the clustering effect [28].

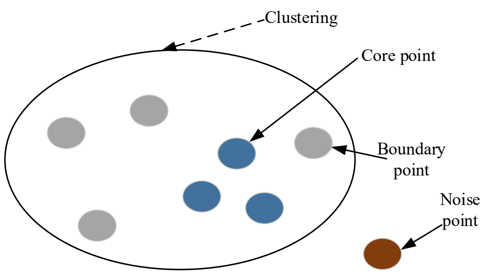


Figure 6. Concepts of core points, boundary points, and noise points.

The DBSCAN process is as follows: Starting from any point p in the database, retrieve all point densities reachable from p under given Eps and Minpts. If p is the core point, the process generates a cluster using Eps and Minpts, and the point is classified; if p is a boundary point, there is no point density-reachable from p, and DBSCAN accesses the next unclassified point in the database [29]. Since DBSCAN defines clusters based on density, it is relatively noise-resistant and can find clusters of arbitrary shapes. Therefore, DBSCAN can find clusters that k-means cannot [30].

3.2. Online Phase

The results of offline clustering are stored in a new location fingerprint database. In the positioning stage, the distance between the label to be tested and the central node of each sub-region is obtained for rough positioning. After that, the fine positioning is finally completed by matching the coarse positioning area. Currently, there are NN, KNN, WKNN, and simple weighted k-nearest neighbor (SWKNN) algorithms for matching algorithms [31]. To maximize its advantages, this paper implements a weighted optimal k-nearest neighbor (WOKNN) algorithm in the positioning stage, that is, the method of selecting the best matching algorithm and its best k value for different regions.

The flow of the SWKNN algorithm is as follows.

1. The receiver obtains the RSS value and calculates its Euclidean distance $\mathrm{d_i}$.

$$\mathrm{d_i} = \sqrt{\sum_{\mathrm{i}=1}^{4} (RSS_{T\mathrm{i}} - RSS_{\mathrm{i}})^2} \tag{7}$$

Among them, RSS_{Ti} represents the RSS value at the undetermined site collected online, RSS_i is the corresponding number from the offline fingerprint database, and i is the subscript of LED;

2. Arrange the distances d_i in ascending order, and find the average value E_d of the nearest K distances.

$$E_\mathrm{d} = \frac{\mathrm{d_1} + \mathrm{d_2} + \cdots + \mathrm{d_k}}{K} \tag{8}$$

3. Compare each distance value d_i with the average value E_d, remove the distance greater than the average value, record the remaining points as M, and replace the K value in WKNN with M;
4. Repeat the above process and gradually reduce the value of K to make it closer to the true value. The estimated position coordinates of the target to be located are:

$$P = \frac{\frac{1}{d_1} L_1 + \frac{1}{d_2} L_2 + \cdots + \frac{1}{d_M} L_M}{\frac{1}{d_1} + \frac{1}{d_2} + \cdots + \frac{1}{d_M}} \tag{9}$$

where P represents the coordinates of the target to be located, and L_i corresponds to the position of i th fingerprint.

4. Simulation Verification and Discussion

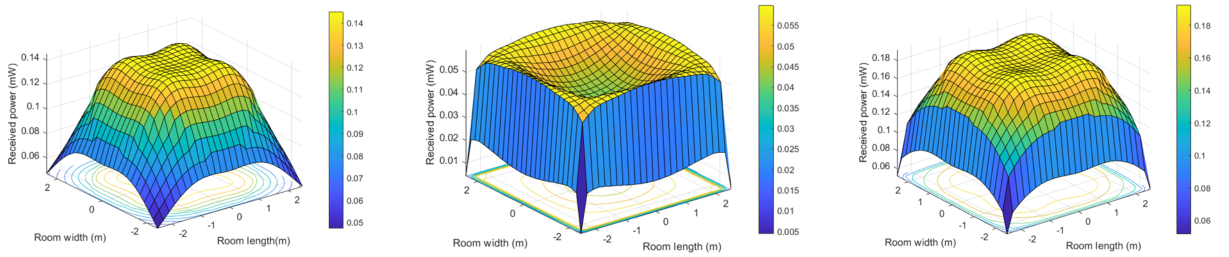
This section starts with the power distribution, considering the impact of diffuse reflection, studies the location error distribution in different areas of the indoor environment, verifies the effectiveness of the proposed algorithm, and some additional conditions are summarized in Table 1.

Table 1. VLP system simulation parameters.

Parameters	Value
Emitting optical power	1 W
Half power angle	60°
Wall reflectivity	0.7
Receiver responsiveness	0.5 A/W
Receiver field of view angle	70°
Refractive index	1.5
Reflection coefficient	0.8
SNR	30 dB

4.1. Fingerprint Method

The LOS channel is very important in almost all indoor VLC positioning systems, because it receives most of the total optical power, as shown in Figure 7a, which shows the power distribution under the LOS link, and the entire receiving surface presents high center and low corners. Figure 7b is the optical power distribution diagram of NLOS, and it can be seen that the distribution of NLOS and LOS channels shows an opposite trend. Since the reflection of visible light always exists in the indoor environment, especially in narrow spaces with walls, ceilings, floors, and some furniture, most of the power added by the NLOS of the scattering part is concentrated near the walls of the room and less in the center, so the center receives the lowest scattered power. Compared with Figure 7a, near the edge of the wall, the scattering power is almost equal to the LOS component. Figure 7c shows the distribution of the total received optical power. Compared with Figure 7a, the overall power distribution of the room is more gentle due to the addition of NLOS energy.



(a) (b) (c)

Figure 7. Distribution of received optical power: (**a**) LOS channel; (**b**) channel with only one reflection; (**c**) total channel.

When the SNR is 30 dB, the distribution of the positioning error of 100 points to be measured is shown in Figure 8, the numbers marked in the figure are the serial numbers of the points to be measured which are evenly selected. It can be seen that the error in the middle area of the room is small, and the error in the corner and edge areas is large. Compared with Figure 7, it can be seen that this is due to the increase in the error caused by the gradual increase in the specific gravity of the scattering component, and the multipath effect will cause the positioning error of the corner and the edge to greatly deteriorate. According to the system simulation calculation, the average positioning error of the whole room is 20.26 cm, and the maximum error at the corners which is greatly affected by reflected light is about 1.15 m. Then, the traditional fingerprint positioning method is improved and its performance is verified.

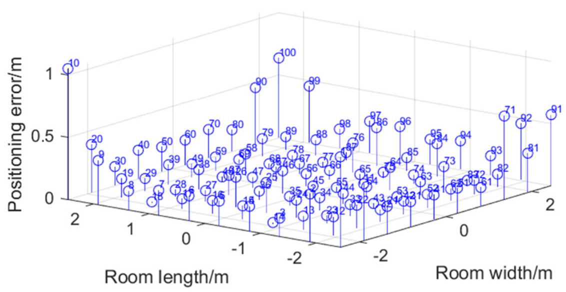


Figure 8. Location error using the fingerprint method.

4.2. Improved Fingerprint Method

The positioning effect is different for different areas. Therefore, the indoor positioning technology based on VLC must take into account the reflected signal and all receiving points are clustered via fusion before positioning. Fusion clustering uses two algorithms to complement each other's advantages to improve its accuracy. The specific fusion clustering effect is shown in Figure 9.

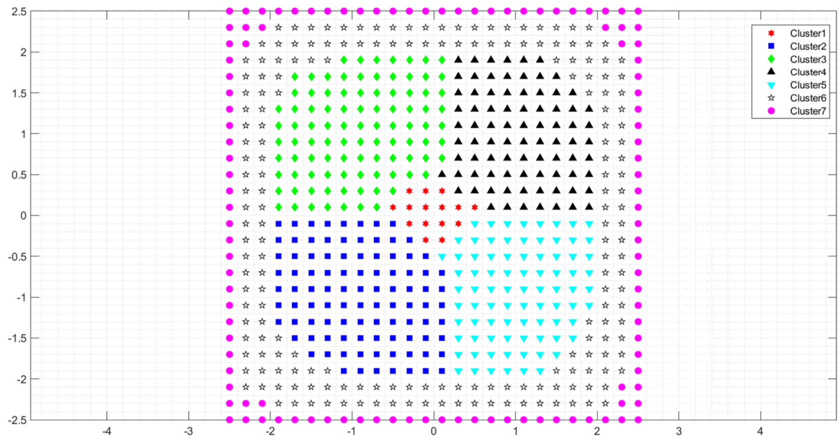


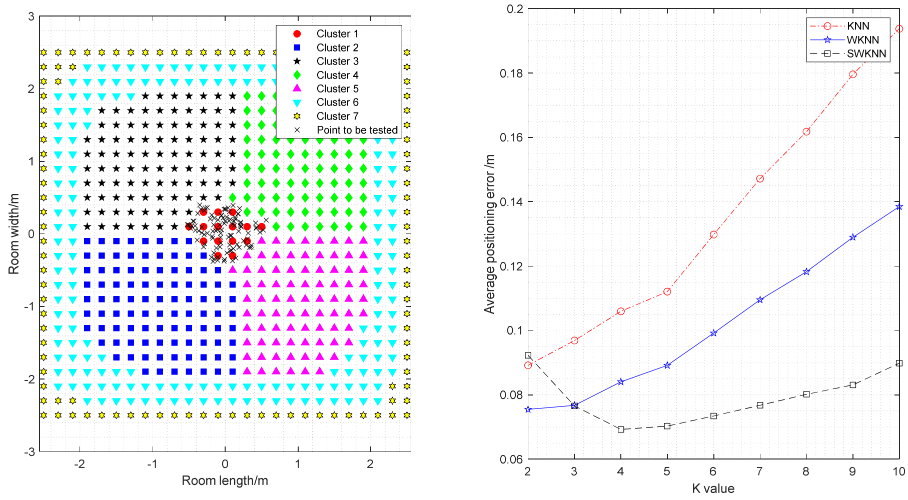
Figure 9. Fusion clustering result diagram.

In the matching positioning stage, the excessive passivity of the number of neighboring points limits the positioning accuracy, because in most cases, the value of k is manually selected and fixed [32]. In fact, the selected value may be well suited for one area, but other areas may need different values. Therefore, optimizing the number of nearest points in each region is a promising solution to improve positioning accuracy. Next, we simulated and analyzed the positioning error of different k values under different algorithms in each area, as shown in Figure 10. For each cluster, from the perspective of overall positioning performance, SWKNN is the best, followed by WKNN, and finally KNN, and as the value of k increases, the error of the matching algorithm will increase, which will also increase the positioning time, so the influence of the k value cannot be ignored. To minimize the average positioning error, it is necessary to determine the algorithm and its neighboring points with minimum error in each region.

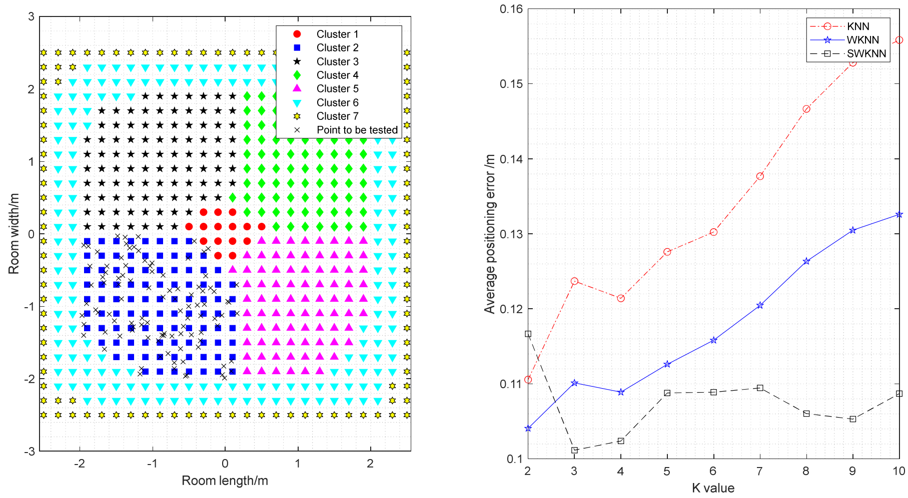
Through cross-validation, the algorithm and k value with the best positioning effect in each cluster are determined. We summarize the results of Figure 9 and present them in Table 2. It can be seen that from the center of the room to the edge, the average positioning error increases from small to large, and the error in each area has been reduced using the clustering algorithm.

Next, we applied the proposed algorithm to locate the points to be measured. Figure 11 shows the error distribution of uniformly selected points to be measured, compared with the traditional fingerprint method, it can be seen that the proposed algorithm effectively reduces the error of the edge part, with a maximum reduction of 0.49 m. It is more accurate for the edge region, partly because of clustering, and partly because the cosine distance is used to measure the points to be measured instead of the traditional Euclidean distance, which can make the estimated value closer to the real value, and the positioning accuracy is most obviously improved at the corners after adjustment. There is little difference in the positioning error in the central area of the room because the central part is not greatly affected by multipath reflection, so the improvement is not obvious. This scheme can effectively solve the defects of large edge and corner errors in traditional RSS positioning, and the proposed algorithm greatly enhances the positioning performance based on VLP.

In order to further evaluate the localization performance of the proposed system, it is compared with the classical algorithm. Figure 12 shows the cumulative distribution function (CDF) of positioning errors of the different algorithms. The results show that the combination of the fusion clustering algorithm and the WOKNN algorithm has higher positioning accuracy than other algorithms. Especially, when the cumulative positioning error distribution is 90%, the average positioning error of NN is 0.43 m, while the error distance of the proposed algorithm is 0.24 m, and the positioning performance is improved by 44.2%, which is obviously improved as a whole.



(**a**)



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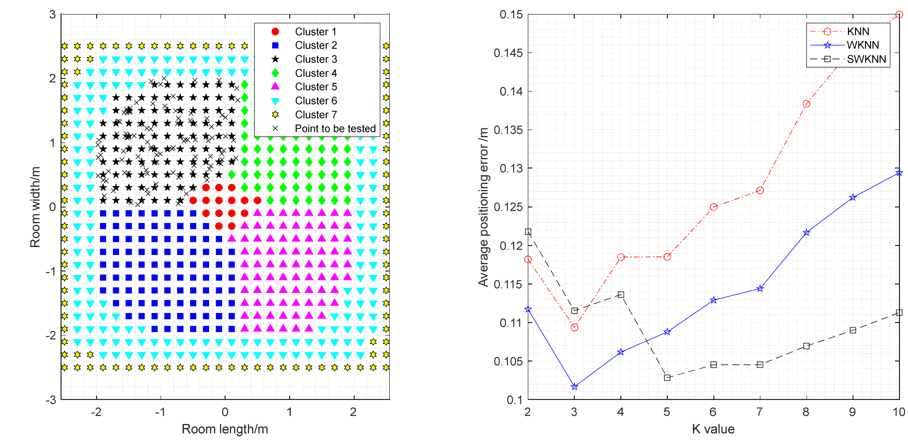
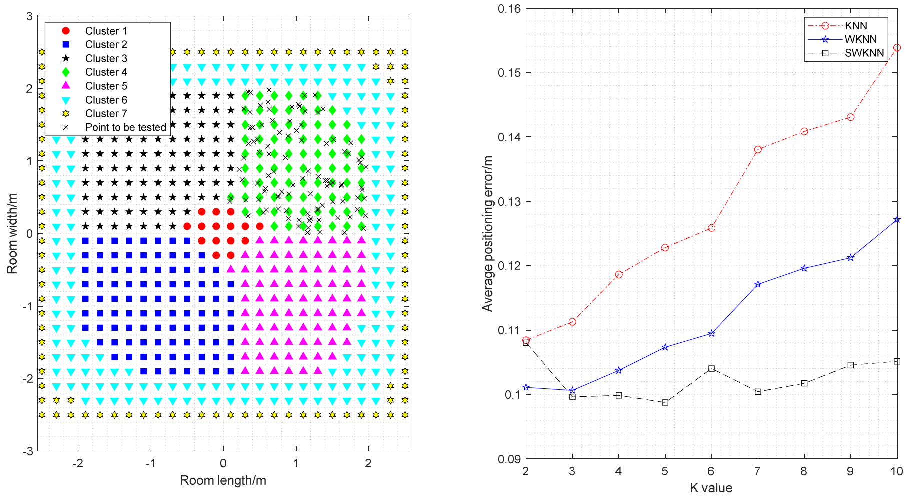


(**c**)

Figure 10. *Cont.*



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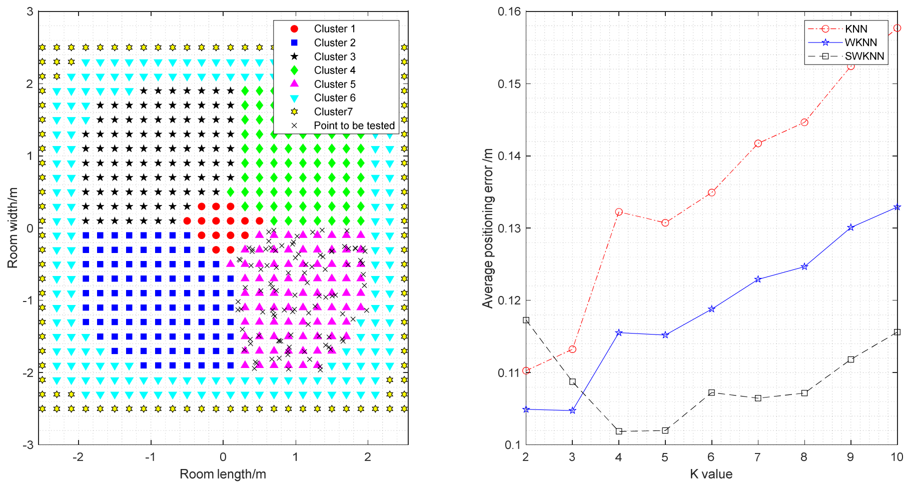

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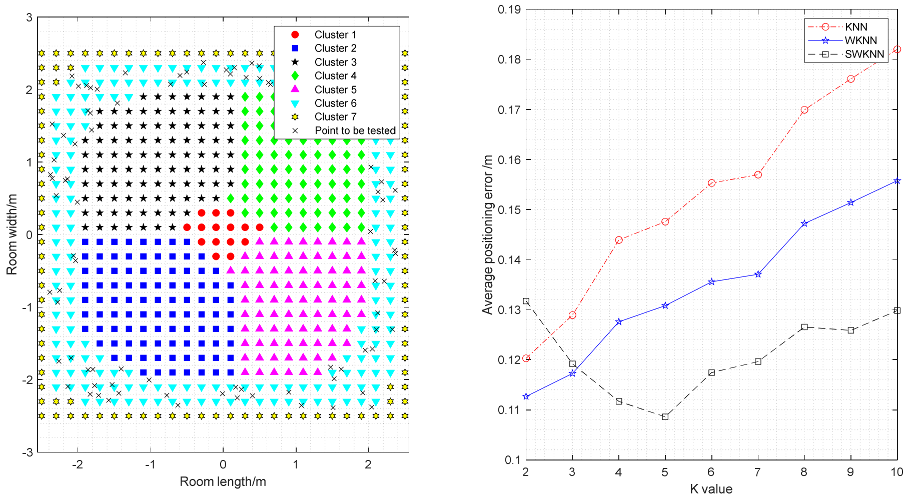
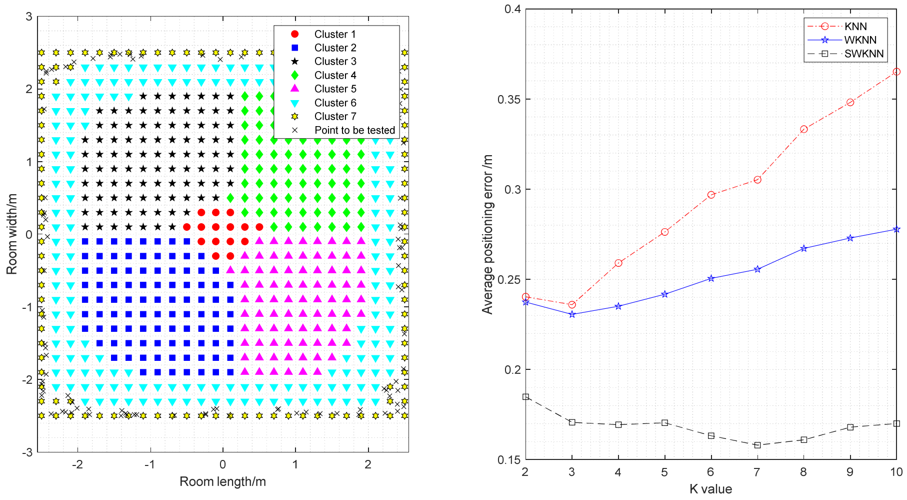


(**f**)

Figure 10. *Cont.*

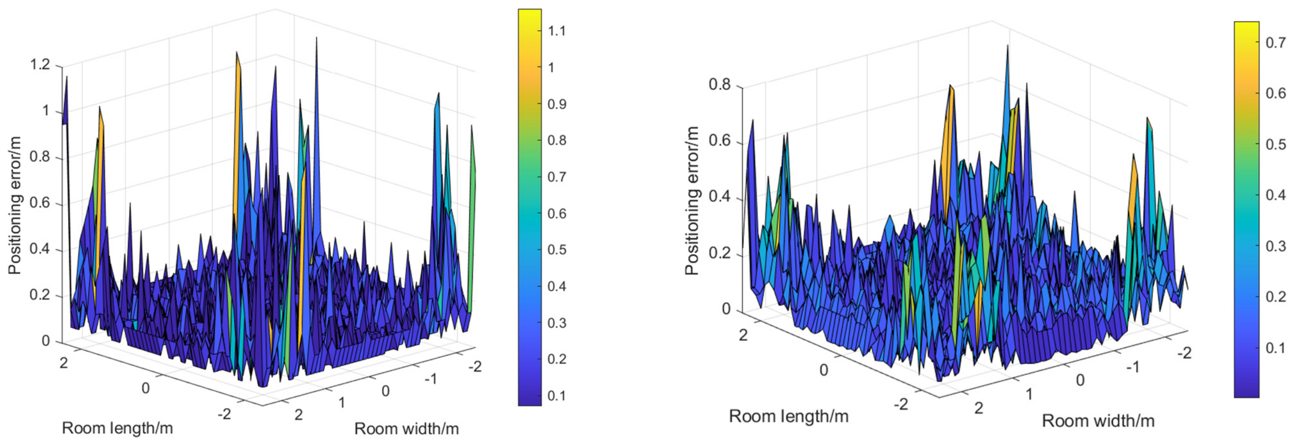


(**g**)

Figure 10. Clustering effect diagram and positioning error of each region: (**a**) Cluster 1; (**b**) cluster 2; (**c**) cluster 3; (**d**) cluster 4; (**e**) cluster 5; (**f**) cluster 6; (**g**) cluster 7.

Table 2. Location results of different clusters.

Region	Optimal Algorithm	Optimum k Value	Average Positioning Error (cm)
Cluster 1	SWKNN	4	6.92
Cluster 2	SWKNN	3	10.11
Cluster 3	WKNN	3	10.16
Cluster 4	SWKNN	5	9.87
Cluster 5	SWKNN	4	10.18
Cluster 6	SWKNN	5	10.86
Cluster 7	SWKNN	7	15.80



(**a**) (**b**)

Figure 11. Location error distribution diagram. (**a**) Traditional fingerprint method; (**b**) proposed algorithm.

Comparing the average positioning error of the proposed algorithm with the traditional algorithm, it can be seen from Table 3 that the positioning effect of the proposed algorithm is better than the other four algorithms. Using the proposed positioning algorithm, the positioning error at the training point can be effectively reduced, and the positioning accuracy of the whole receiving surface is improved by 33.8%, which demonstrates the effectiveness of our method. The improved algorithm proposed in this paper has greatly improved the clustering accuracy.

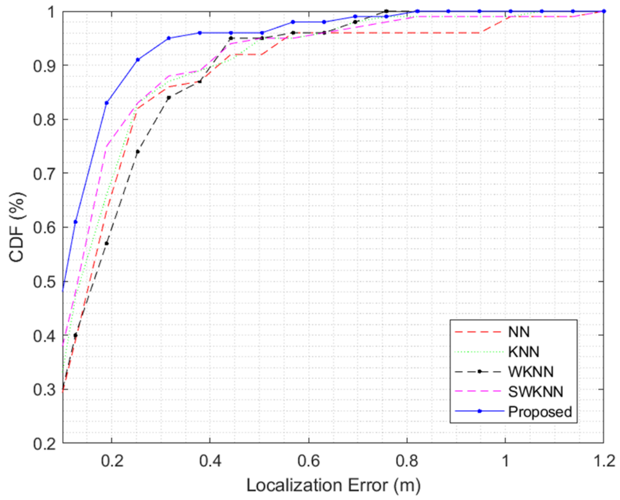


Figure 12. Cumulative probability of errors in different algorithms.

Table 3. Comparison of positioning accuracy of the different positioning methods.

Algorithm	Average Positioning Error (cm)
NN	20.26
KNN	18.51
WKNN	19.87
SWKNN	17.37
Proposed	13.41

4.3. Discussion

The improved fingerprint method divides the research area into multiple clusters and analyzes each cluster separately to determine the optimal algorithm and k value. The algorithm proposed in this paper is effective for most of the light source distributions showing central symmetry. However, as the indoor environment becomes more complex in the future, the changing environment will definitely increase the failure of the fingerprint database, and the focus should be on improving the maintenance and updating the efficiency of the fingerprint database. By selecting a special location as a monitoring point for detecting fingerprint data fluctuations, a backup fingerprint library for common environments can be developed to update the fingerprint library in time. Clustering is also conducive to the analysis of local features to a certain extent and can provide a reference for future compensation schemes. Therefore, in order to improve the practicability of indoor visible light positioning, fingerprint database maintenance and update technology should be strengthened in the future.

5. Conclusions

In this paper, a novel fusion clustering positioning model using visible light is proposed. By combining k-medoids with the DBSCAN clustering algorithm, the high localization performance of the k-medoids algorithm can be utilized while solving the noise problem. This method of clustering first and then positioning is also suitable for complex indoor environments. Coarse positioning improves positioning efficiency, and fine positioning ensures high positioning accuracy, which significantly improves the overall performance, and the positioning performance of the whole room is improved by 31% compared with the traditional algorithm. The accuracy of this method is verified through simulation and algorithm comparison. In the follow-up work, we should consider the adaptive calibration method to improve the positioning effect of corners, and better integrate different positioning technologies to overcome the limitations of single positioning technology.

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