Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 8, No. 4, 1617-1629
2024
Publisher: Learning Gate
DOI: 10.55214/25768484.v8i4.1532

Logistics distribution model and storage planning design based on multi-source information positioning in smart city development

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Abstract: The research mainly focuses on the inefficient planning of autonomous distribution and storage modes of distribution vehicles in smart city logistics and distribution, which in turn leads to poor customer experience, rising distribution costs, and wasted distribution resources. From the perspective of information processing in the logistics distribution process, the study takes multi-angle and multi-source information collection and fusion processing strategy as the main basis to help smart delivery robots realize map construction and autonomous positioning in the distribution process, and then facilitate real-time logistics distribution and storage mode planning by robots in combination with their own states. The research results show that the algorithm accuracy, standard error, and average running time of the extended Kalman filter localization model designed in the study are 0.96, 1.52, and 105s, respectively, with the algorithm accuracy being the highest and the other two values being the lowest in its class. Meanwhile, in the simulation logistics planning, the research-designed logistics planning model has the strongest information capturing ability, and the planning of distribution routes and storage modes is more reasonable, which can provide more efficient autonomous planning solutions.
Keywords: *Distribution model; Logistics; Multi-source information positioning; Smart city; Warehousing.*

1. Introduction

With the development of information technology and the continuous promotion of the smart city process, the logistics industry, as an important part of the green smart city, must improve its own service methods and enhance its service level according to the increasing service needs of users, and improving the efficiency of logistics is one of the important ways to improve the service level[1-3].In intelligent logistics distribution, the planning of intelligent distribution and intelligent storage is the main link of distribution. The intelligent distribution vehicle needs to continuously collect external information during the distribution process, select the distribution route according to the external information, and formulate the storage plan, so as to achieve a more efficient distribution effect with less resources[4-6]. In this automated logistics and warehousing planning, the reliability of external information collection and processing means is crucial, and multi-source information positioning, as a multi-angle information collection and processing technology, can provide sufficient information support for intelligent logistics[7-9] . The multi-source information fusion processing method is mainly a technical means to process the external information using multiple sensors or multiple information source systems. This means measures the current state of the information acquisition target through different information sources, and uses information correlation, information integration and other means to determine the current comprehensive state of the information acquisition target based on the information from different sides, This technology has high accuracy and fault-tolerance, low cost of information acquisition and high reliability, and has been widely used in such fields as military, industrial, transportation and so on. Therefore, this study applies multi-source information positioning

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technology to intelligent city logistics distribution, and provides a feasible path for the realization of automatic logistics distribution planning by using the information collection stability and comprehensive information collection ability of multi-source information fusion positioning technology itself.

2. Related Work

The multi-source information localization technology has been applied in indoor localization and outdoor complex environment localization, and Tang H's team has designed a multi-source information fusion indoor localization method based on wireless LAN. The method is based on inertial navigation system and uses WLAN to enhance the signal strength and design a sparse signal-based fusion model. The researchers finally tested the performance of the positioning model using simulation experiments, and the results showed that the algorithm is robust and effective.[10] . He Z M et al. applied point cloud recognition technology and electric equipment identification technology to a multi-source information integrated indoor positioning system, and also used GPS and other devices as technical aids to achieve accurate positioning and integrated positioning at the decimeter level in indoor and outdoor environments. The experimental results show that the method has high positioning accuracy[11] .Huang L team designed a smart phone positioning technology for indoor pedestrian positioning. Based on the non-line-of-sight problem and multi-path problem of indoor positioning, this technology designs an indoor spatial position learning model based on deep convolution neural network, which forms a nonlinear mapping with wireless network ranging information technology, and then carries out high-precision positioning of indoor pedestrian position through fingerprint positioning. A large number of tests have been carried out on the model, and the research results show that the method has high continuous positioning ability in practical applicationss[12] . Na W et al. proposed a fault location method based on the traditional particle swarm algorithm for the problems of low localization accuracy and slow localization speed in the traditional distribution network fault location process, and the researchers introduced a variable inertia weight factor based on the traditional particle swarm algorithm to The researchers introduced a variable inertia weight factor to adjust the number of iterations based on the traditional particle swarm algorithm, and added a particle screening mechanism to retain the particles with high adaptability. The results show that this method can achieve distribution network fault location detection more rapidly and accurately.[13] . Hu E's team proposes an indoor and outdoor multi-source data localization technique based on inertial high-altitude system, which adopts a relative entropy Kalman strategy to design a multi-source data fusion localization model and filter and outlier processing for multi-source data to improve the reliability and stability of the data. The study also quantifies the degree of coupling of information in the information layer to facilitate the improvement of coupling in the data fusion process. The research results show that the method significantly improves the positioning accuracy and navigation stability of the positioning system. It can be seen that the application of multi-source information in various types of positioning has been relatively mature[14] .

On the other hand, many research results have emerged in recent years in the logistics distribution mode. liu C team analyzed the distribution route and storage planning split in the process of smart urban UAV logistics distribution, and studied the use of multiple UAV communication network linkage to solve the network resource allocation problem, and carried out real-time planning of UAV distribution and storage problem by simulated annealing algorithm to achieve the The planning effect is maximized under the minimum resource allocation. The results show that this method can effectively reduce the resource utilization rate in practical applications.[15] . Chan F T S team proposes a multi-objective particle swarm optimization algorithm for food logistics distribution and warehousing, and then builds a smart food logistics system based on it. The system can effectively reduce the total cost of the logistics system, maximize the average quality of the food logistics, minimize the carbon dioxide emissions in the food logistics and distribution process, and shorten the overall delivery time of the logistics.[16] Safaei AS team proposed a logistics distribution and storage mode planning model for relief materials in critical situations. The model can minimize the overall operating cost of relief materials in the distribution process, and meet the distribution needs of materials. The model is solved by objective programming method, and the results show that the model can meet the emergency distribution needs under the corresponding scenarios[17] . Musolino G's team proposed a logistics distribution planning method based on the location of urban intelligent distribution centers, and analyzed the effect of logistics operation under the route and storage planning by means of simulation tests. The research results show that the strategy can effectively guarantee the sustainability of logistics operations[18] . It can be seen that the current research on logistics distribution and storage planning is more focused on real-time dynamic planning, focusing on intelligent improvement of the city, but this dynamic planning is particularly dependent on the information collection and processing capabilities of the system, so the research selects the multi-source information positioning technology with better information processing effect as the basis to establish the intelligent logistics distribution model and storage planning model, Provide a feasible path for the realization of intelligent logistics distribution.

3. Multi-Source Information Positioning Logistics Automated Warehousing and Distribution Model Design

3.1. Map Construction and Positioning Navigation Strategy Design

In intelligent logistics warehousing and distribution, the distribution system needs to choose the logistics and distribution mode and plan the storage strategy based on the lack of detailed information and the overall terrain is unstructured and complex in elements. In the planning process, the distribution system needs to capture external information from multiple sources, and this information is often captured through different kinds of sensors. On the basis of fully acquiring external information, the system can construct a map through algorithms and realize positioning on this basis, and then realize automated distribution mode and storage mode planning, and the specific process is shown in Figure 1.

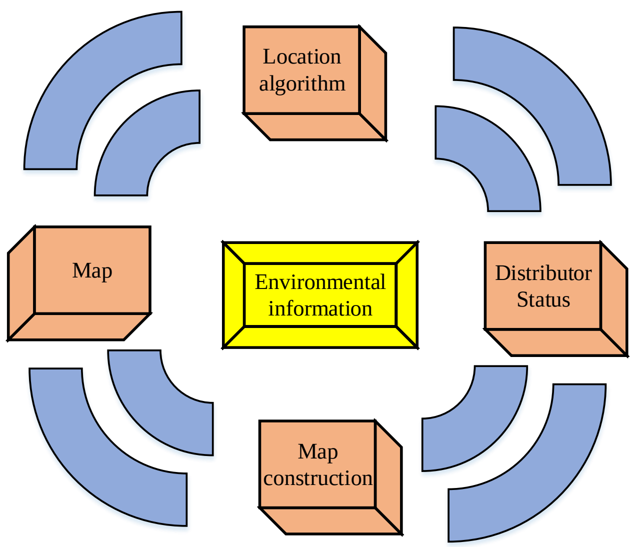

Figure 1.
Map creation and positioning process.

Intelligent logistics warehouse planning and distribution process are interdependent on the distribution mode planning, which in turn is strictly based on the specific environmental information in the planning area. This process, shown in Figure 1, is a combination of algorithmic positioning and system map construction. In this process, the intelligent distribution system gradually builds incremental environmental maps through the collection of external environmental information by sensors. At the same time, the real-time location of itself in the map is continuously positioned during the real-time distribution process. This process can be succinctly divided into four main implementation steps: map creation, information feature extraction, map location matching, and distribution state correction. Since all these steps are based on the sensor information capture of the delivery robot, if the external information is not sufficient, it will lead to problems in delivery planning. Therefore, this study uses multi-sensor information fusion for information extraction to ensure that the delivery robot collects sufficient information about the external environment. The specific system framework is shown in Figure 2.

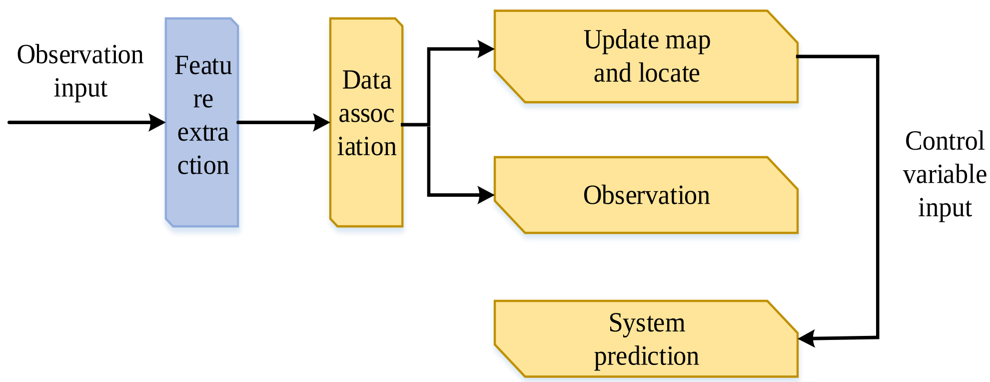

Figure 2.
Navigation system framework.

In this study, the extended Kalman filter algorithm is selected as the main algorithm to solve the map construction and localization problem based on the consideration of robustness and accuracy in the process of external environment information collection. Through the extended Kalman filter algorithm, the study constructs a planar coordinate system in the process of map construction and localization, and uses the point coordinates in the planar coordinate system to represent the location of the distribution point and the surrounding environment information, and describes the distribution mode of the distribution point, its relationship with the external environment information as a nonlinear model with motion. Considering map construction and localization as a filtering problem, then the noise in the system can be processed using the extended Kalman filter algorithm, and the nonlinear discrete control system equations of the algorithm are shown in Equation (1).

$$X(k)=F\left[X(k-1)\right] \tag{1}$$

In Equation (1), $X(k-1)$ represents the vector formed by the system state at the moment of $k-1$, and F represents the system parameters. The observation equation is shown in Equation (2).

$$Z(k)=H\left[X(k)\right]+V(k) \tag{2}$$

In Equation (2), H denotes the observation system parameters and $V(k)$ denotes the system noise vector. It is important to update the distribution status and environmental information of the distribution point in the process of map construction and positioning. The data collected by the sensor synthesis is used as the input control quantity, and the distribution status of the distribution point is observed and updated based on the current location of the distribution point. Firstly, the location of the distribution point in the map is determined by using the extended Kalman filtering algorithm, after that, the information of the environmental features around the distribution point is collected, and the real-time map information and location information are updated by using the fitness equation, and finally the deviation value is reduced in a circular iterative manner. The current moment is represented by k, then the current system state and the previous one are shown in Equation (3).

$$\begin{cases} X(k|k) \\ X(k-1|k-1) \end{cases} \tag{3}$$

The prediction process of the system focuses on the estimation of the prior and variance at k using the measured values and variance of the system at $k-1$. The specific process is shown in Equation (4).

$$P(k|k-1) = \nabla F_x(k) P(k-1|k-1) \nabla^T F_X(k) + Q(\mathrm{k}) \tag{4}$$

In Equation (4), P denotes the variance, $P(k-1|k-1)$ denotes the corresponding variance formed by the optimal value at the previous time, while $P(k|k-1)$ denotes the corresponding variance formed by the estimated value at the current time, $Q(\mathrm{k})$ denotes the variance mapping formed by the noise generated in the system, and F denotes the system parameters. When the system updates the map and positioning information, it mainly uses the estimated value at the moment of k and the corresponding variance value formed by the estimated value for the system update, as shown in Equation (5).

$$\hat{X}(k|k) = \hat{X}(k|k-1) + W(k)\left[Z(k) - H\left(\hat{X}(k|k-1)\right)\right] \tag{5}$$

In Equation (5), H denotes the observation system parameters, $Z(k)$ denotes the observation vector, and $W(k)$ can be calculated by Equation (6).

$$W(k) = P(k|k-1) \nabla^T H_X(k) S^{-1}(k) \tag{6}$$

And $S(k)$ in equation (6) can be further calculated using equation (7).

$$S(k) = \nabla H_X(k) P(k|k-1) \nabla^T H_X(k) + R(k) \tag{7}$$

In Equation (7), $R(k)$ denotes the update vector. The extended Kalman filter algorithm application strategy used in the study not only makes the map construction and localization of automated logistics planning easier to implement, but also enables highly accurate and efficient real-time localization. The schematic diagram of distribution planning and localization based on sensor multi-source information fusion is shown in Figure 3.

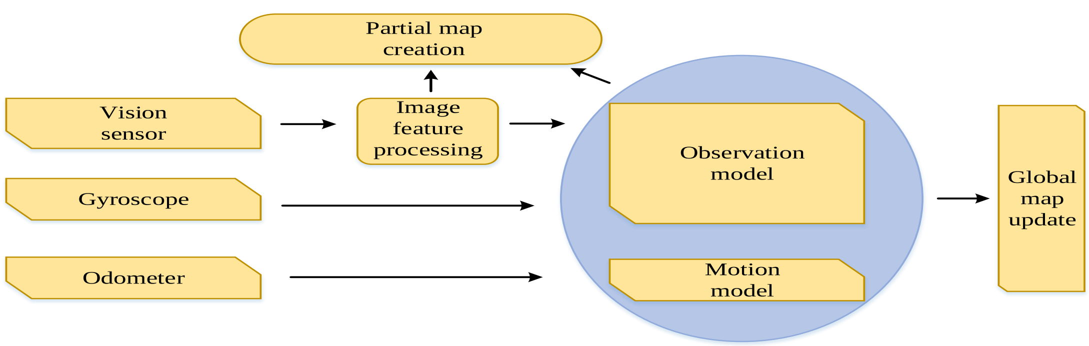

Figure 3.
Multi-source information fusion model.

As can be seen in Figure 3, the study uses odometers for location recording of distribution points in multi-source information acquisition, gyroscopes for attitude recording of the intelligent distribution vehicle, and vision sensors for peripheral image information acquisition and processing. The multi-source information acquisition is used to realize the automated distribution model and storage planning. Therefore, it is necessary to design a multi-source information synthesis model to perform multi-source fusion processing of the collected information.

3.2. Multi-Source Information Aggregation Model Design

The research and design of the multi-source information synthesis model mainly adopts three forms of information collection, namely, intelligent distribution vehicle odometer, gyroscope and visual sensor. In the process of intelligent logistics and distribution, the real-time planning of distribution mode and storage mode depends on the change of distribution environment information, and the optimal distribution and storage planning scheme is often different under different information backgrounds. Multi-source information fusion in the form of multi-sensor can effectively reduce the redundancy and contradiction of information, and achieve information complementarity and information verification. In the typical information fusion model, the sensor information collection is the basis of the information prior model. The model provides the basis for decision-making through data matching, data association and data fusion of the collected data. However, the typical information fusion model has insufficient ability to extract information features, which easily leads to information distortion and information confusion. Therefore, this study uses the optimized multi-layer information fusion model for information processing, and the specific architecture is shown in Figure 4.

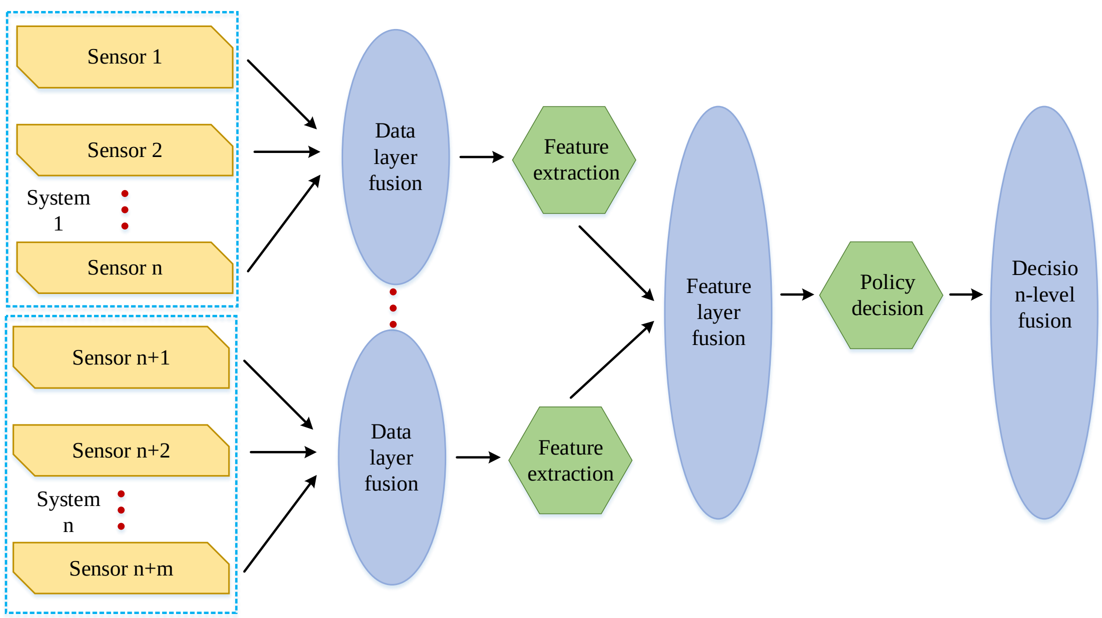

Figure 4.
Multi-layer information fusion model.

As can be seen from Figure 4, the multilayer information fusion processing strategy used in the study extracts external data features by performing data fusion at the data layer for each sensor subsystem, and then fuses the data features of each subsystem at the feature layer, and finally performs information fusion at the decision layer based on the whole layer of data. In the information fusion process, the most common is the centralized information fusion structure, which is a fusion structure with a central information fusion center as the main structure. Based on this, a distributed information fusion structure with multiple local information fusion centers has evolved. In this study, two information fusion strategies are combined to form a hybrid information fusion structure, which adds a central information fusion center on top of the distributed information fusion structure to aggregate and fuse the information from multiple local information fusion centers, as shown in Figure 5.

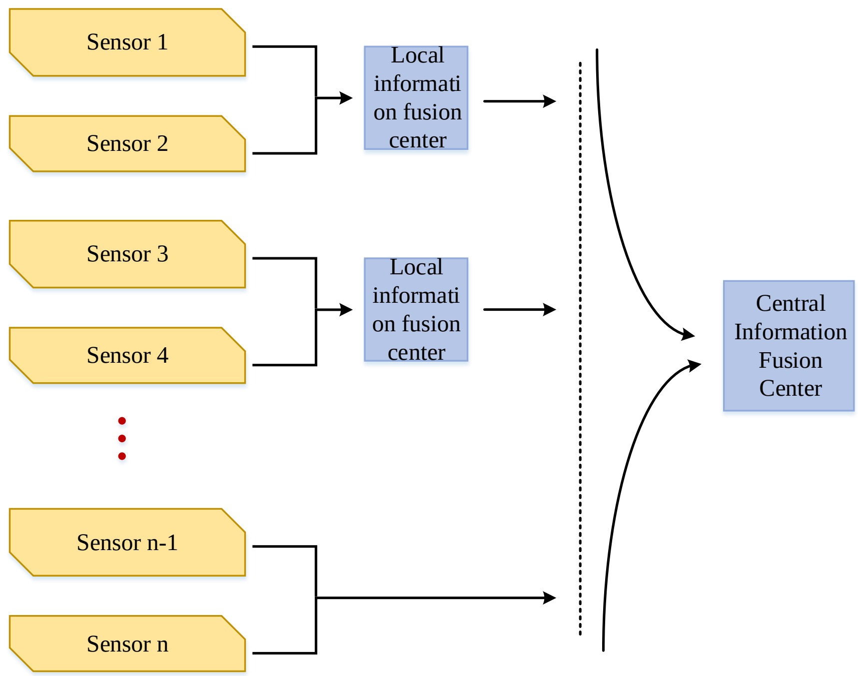

Figure 5.
Information fusion processing structure.

As can be seen from Figure 5, the hybrid information fusion structure used in the study can use local information fusion centers to pre-process external information. After pre-processing by multiple local information fusion centers, the information as a whole has formed preliminary fusion characteristics, and on this basis, information fusion is conducive to improving the efficiency of information utilization, reducing information loss, and making information more accurate. Since the distribution point is in constant motion during the real-time planning of distribution and storage mode, the odometer and gyroscope may produce certain motion deviation for the collection of environmental navigation information. However, using only vision sensors for data acquisition can lead to inefficient and time-consuming data processing. Therefore, the study uses the vision sensor as an absolute sensor and the odometer and gyroscope as relative sensors. The Kalman filter module of the local data fusion center directly oriented to the sensor information can measure the system state based on the real-time state of the smart delivery vehicle, and the system state equation is shown in Equation (8).

$$\sigma_1(k)=\sigma_1(k-1)+\frac{U(k-1)}{D}+V(k-1) \tag{8}$$

In Equation (8), σ represents the attitude deviation, V represents the velocity, $k-1$ and k represent the two immediately adjacent moments, D represents the wheel distance, and $\sigma(k)$ can be calculated using Equation (9).

$$\sigma(k)=\sigma(k-1)+\Delta\sigma(k) \tag{9}$$

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ISSN: 2576-8484
Vol. 8, No. 4: 1617-1629, 2024
DOI: 10.55214/25768484.v8i4.1532

And $\Delta\sigma$ in equation (9) can be calculated using equation (10).

$$\Delta\sigma = \frac{(V_1 - V_2)\cdot \Delta T}{D} \tag{10}$$

In Equation (10), V_1 and V_2 denote the speed of the two driving wheels, respectively, and T denotes the time. The system observation equation can then be expressed in the form of Equation (11).

$$Z(k) = H\sigma_g(k) + V(k) \tag{11}$$

In Equation (11), $V(k)$ denotes the measurement noise, H denotes the unit matrix, and $\sigma_g(k)$ denotes the angular velocity measured by the sensor. k The predicted value of the system state at the moment can be calculated using Equation (12).

$$\sigma t(k|k-1) = \Delta V(k-1)/D \tag{12}$$

On this basis, the corresponding variance values can be calculated, and the calculation procedure is shown in Equation (13).

$$P_t[k|k-1] = P(k-1|k-1) + Q(k) \tag{13}$$

By bringing the measured and estimated values of the odometer and gyroscope at k into the system update equation, the optimal solution of the system at that moment can be obtained, as shown in Equation (14).

$$\sigma(k|k) = \sigma t(k|k-1) + Kg(k)(\sigma g(k) - \sigma t(k|k-1)) \tag{14}$$

In turn, the covariance corresponding to the optimal solution of the system at the moment can be calculated, as shown in Equation (15).

$$P(k|k) = (1 - Kg(k))Pt(k|k-1) \tag{15}$$

Taking the local fusion processing results of odometer and gyroscope as the input of the central information fusion center, and then taking the data acquisition results of visual sensor as the direct input, the constellations can complement each other in the fusion process and improve the effect of positioning accuracy.

4. Multi-Source Information Positioning Logistics Automated Warehousing and Distribution Model Effect Verification

When verifying the effect of the multi-source information positioning logistics automatic warehousing and distribution model, the performance of the Kalman filter positioning model used in the study was compared and analyzed first, then the error was compared and analyzed from the perspective of different sensor use and different information fusion methods, and finally the real-time positioning and logistics planning simulation were carried out in the actual environment. In the part of model performance analysis, the research mainly analyzes the algorithm accuracy, standard error and average running time. The research mainly compares the extended Kalman filter positioning model designed this time with the Kalman filter positioning model, particle filter positioning model and Bayesian filter positioning model. The specific results are shown in Figure 6.

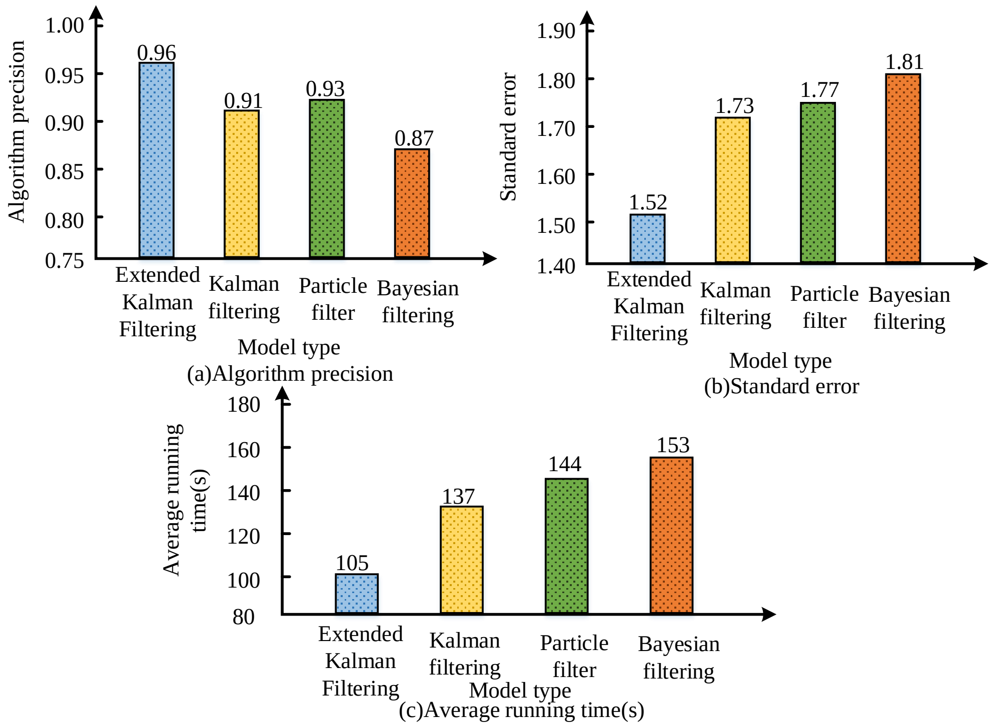

Figure 6.
Model data comparison.

From Figure 6, we can see that, in terms of algorithm accuracy, the algorithm accuracy of this designed extended Kalman filter localization model reaches 0.96, the algorithm accuracy of Kalman filter localization model is 0.91, the algorithm accuracy of particle filter localization model is 0.93, and the algorithm accuracy of Bayesian filter localization model is 0.87. The algorithm accuracy of this designed extended Kalman filter localization model is the highest and the model In terms of standard error, the standard error of the designed extended Kalman filter localization model is only 1.52, the standard error of the Kalman filter localization model is 1.73, the standard error of the particle filter localization model is 1.77, and the standard error of the Bayesian filter localization model is 1.81. The standard error of the designed extended Kalman filter localization model is the lowest and the localization In terms of the average running time, the average running time of the extended Kalman filter localization model is 105s, the average running time of the Kalman filter localization model is 137s, the average running time of the particle filter localization model is 144s, and the average running time of the Bayesian filter localization model is 153s. 105s is the lowest and the most efficient operation. It can be seen that, compared with the same type of models, this designed extended Kalman filter localization model shows significant performance advantages in terms of algorithm accuracy, standard error and average running time. The next study compares the errors generated under four types of information processing: relative sensor information processing alone, absolute sensor information processing alone, local center information fusion processing, and overall information fusion processing, and the analysis results are shown in Figure 7.

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Vol. 8, No. 4: 1617-1629, 2024
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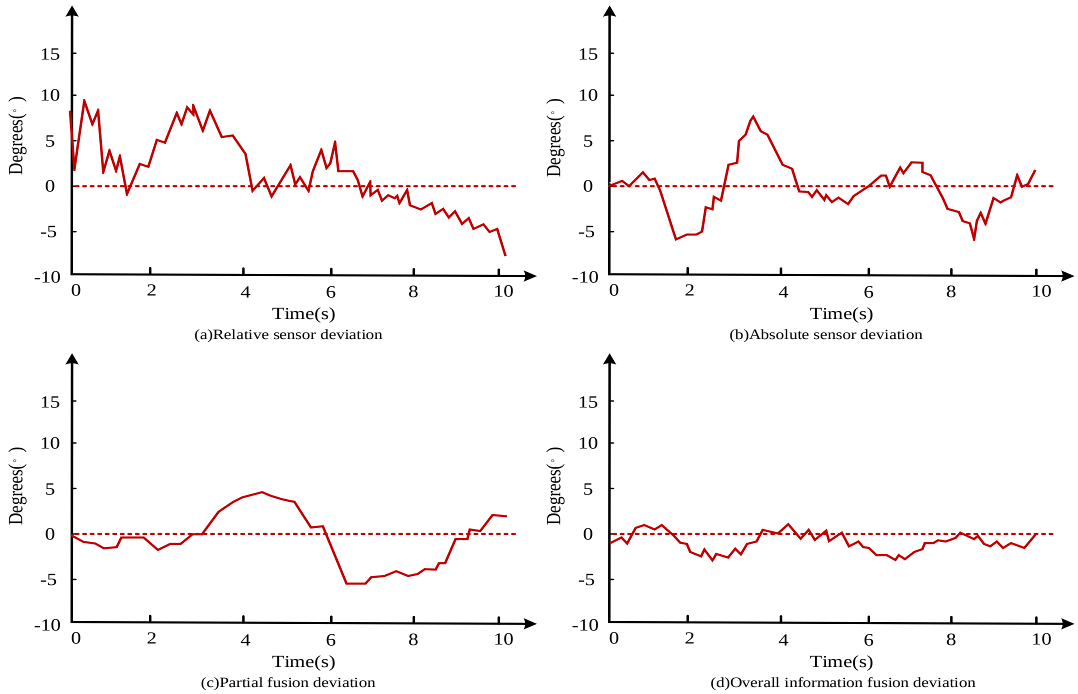

Figure 7.
Error comparison analysis.

As can be seen from Fig. 7, the variation interval of the localization deviation line is larger under both the individual relative sensor information processing strategy and the individual absolute sensor information processing strategy, and the fluctuation of the line is frequent and violent, and the deviation distance is larger than that of the baseline. Compared with the individual relative sensor information processing strategy and the individual absolute sensor information processing strategy, the fluctuation of the localization deviation line under the local center information fusion processing strategy is no longer frequent, but the fluctuation magnitude is still violent and the fluctuation interval is larger. In contrast, the fluctuation of the localization deviation line under the overall information fusion processing strategy adopted in this study is significantly reduced compared with the other strategies, and the overall line is closer to the baseline and varies up and down around the baseline. This demonstrates that the overall information fusion strategy can significantly reduce the localization bias. In the simulation test, the study made a series of prior settings for the map environment, movement patterns and other elements of the logistics distribution, as shown in Table 1.

Table 1.
Simulation test settings.

Simulation test elements	Simulation environment	Environmental parameters
Map elements	Two-dimensional flat areas	The area plane is 100m*100m unit, containing a total of 34 feature points
Motion model elements	Encoder class model	\
Observation model elements	Visual sensing observation model	Observation distance 2m, observation interval 0.2s
Model noise elements	Gaussian noise environment	Noise value is 0

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As can be seen from Table 1, the map environment of the simulated distribution is mainly presented in a two-dimensional plane and there are 34 information feature points in the simulated environment, while the Gaussian noise value of the model is 0. The positioning error condition of the system with different sensors turned on is shown in Figure 8.

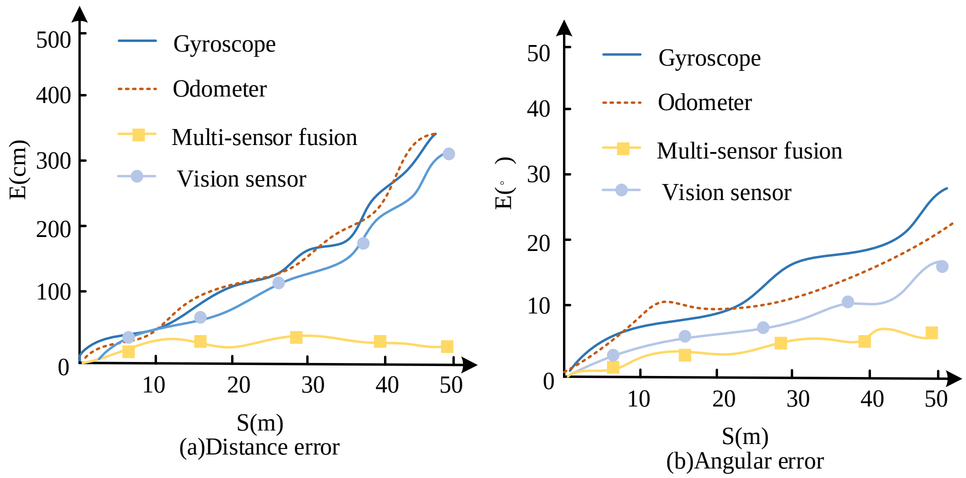

Figure 8.
System positioning error under different sensors.

It can be seen from Figure 8 that in terms of distance error, the distance error curves of gyroscope and odometer are not significantly different, and both show a trend of rising with the increase of distance. At the same time, the two do not show a significant difference in the overall error trend. Compared with gyroscope and odometer, the position of distance error curve formed by visual sensor is relatively lower, and the average error formed by visual sensor is relatively smaller. However, the distribution position of the range error curve formed by the multi-sensor model designed in this study is significantly lower than that of the first three, and different from the first three curves, the range error polyline of the multi-sensor model does not show a rising trend with the increase of the navigation distance, which proves that the multi-sensor model designed in this study has more advantages in accuracy and stability in terms of range error; In terms of angle error, the angle error curves of gyroscope and odometer are similar, showing a trend of rising with the increase of distance, and the two also do not show a significant difference in the overall error trend. Compared with gyroscope and odometer, the position of angle error curve formed by visual sensor is relatively low, and the average error formed is relatively small. The distribution position of the angle error curve formed by the multi-sensor model designed in this study is significantly lower than that of the first three. Although the broken line also shows an upward trend, the trend is not significant, which proves that the multi-sensor model designed in this study is also more advantageous in accuracy and stability in terms of angle error. The final logistics distribution and warehousing mode planning results are shown in Figure 9.

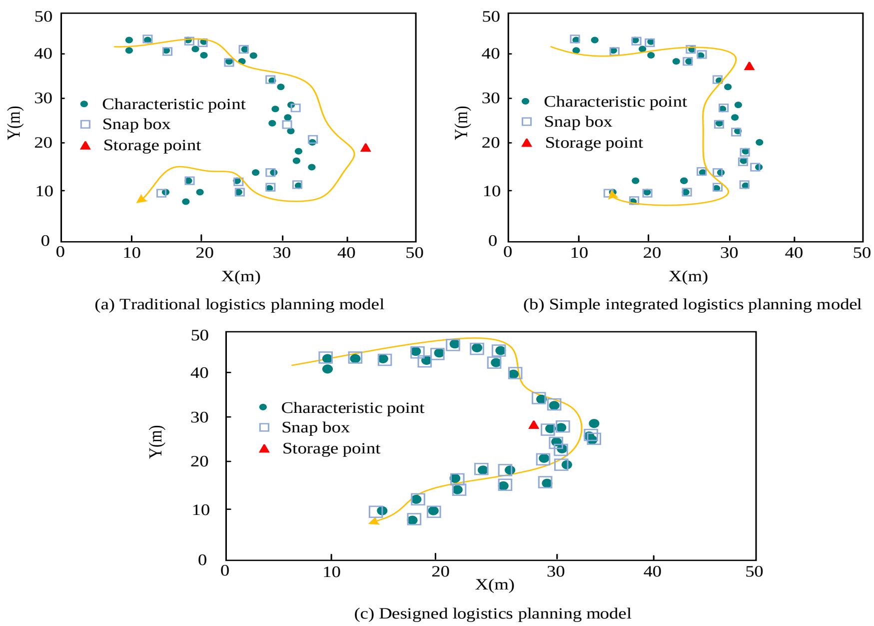

Figure 9.
Comparison of logistics planning effects.

From Figure 9, we can see that the traditional logistics planning model does not successfully capture all the information feature points, but only nearly half of them, and the planned distribution route deviates from the information feature points significantly, which makes it difficult to achieve efficient distribution, and the planned storage points are also far away; in comparison, the single information sensing logistics planning model has a higher success rate of capturing information feature points, and the planned distribution In contrast, the single information sensing logistics planning model has a higher success rate in capturing information feature points, and the planned distribution routes also show a trend of convergence, and the route efficiency is higher than that of the traditional logistics model, but the routes still show a blind separation from information feature points, and the storage point planning does not take into account the balance of the distance between the starting point and the end point; while the multi-source information location distribution planning model designed in the study can accurately capture most of the information feature points, and the planned routes are closely adjacent to the information feature points, and the overall route efficiency is higher. The overall route efficiency is high. At the same time, the storage point locations planned by the model are more conducive to the efficient allocation of routes. This shows that the multi-source information location distribution planning model designed by the research has stronger advantages in distribution model and storage planning.

5. Conclusion

The study focuses on the inefficient planning of autonomous distribution and storage modes of distribution robots in smart city logistics and distribution, which leads to poor customer experience, increased distribution costs, and wasted distribution resources. From the perspective of information processing in the logistics distribution process, the study takes multi-angle and multi-source information collection and fusion processing as the main basis to help smart delivery robots realize map construction and autonomous localization in the distribution process, and then combine their own state for real-time logistics distribution and storage mode planning. The research results show that the algorithm accuracy of the extended Kalman filter localization model designed in the study reaches 0.96, which is the highest value in its class, and the standard error is only 1.52, which is the lowest value in

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its class, and the average running time is only 105s, which is the lowest value in its class, showing that the model has performance advantages. Meanwhile, in the simulation, the multi-sensor model designed in the study has more advantages in distance error and angle error, and has better information capture capability compared with other logistics planning models. has only two information capture failures, and the overall route and storage planning is more reasonable, which can carry out more efficient route planning.

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