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A SLAM and Deep Vision Computing-based Robotic Path Planning Method for Agricultural Logistics Warehouse Management

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The advent of "Industry 4.0" has led to rapid advancements in robotics technology. Inspection robots are widely used in several areas, such as aerospace, manufacturing, agriculture, and service industries, because of their outstanding functionality, mobility, and flexibility. Deployment of robotic systems can improve agriculture warehouse management efficiency. Nevertheless, the presence of impediments within warehouses creates a highly intricate environment that restricts the potential advancements in current research. This study presented a new approach to robotic path-planning for agricultural logistics warehouse management by combining Simultaneous Localization and Mapping (SLAM) with deep vision computing. The utilization of SLAM technology enables the achievement of autonomous positioning of robots in warehouses. SLAM, or Simultaneous Localization and Mapping, is a technique that allows a robot to estimate its own position while also creating maps of its surroundings. This process provides essential data that may be used for planning the robot's journey. Robots may utilize advanced technologies like LiDAR and sensors to accurately detect their surroundings and create detailed maps in real-time. Next, the implementation of deep vision computing technology is presented in order to achieve the recognition and analysis of objects within the warehouse. The optimization of robot path is achieved using SORF, and a layer for pooling robot position-sensitive areas is established with adaptive weighting. At last, the tasks of improving the image quality and determining the optimal path have been successfully finished. An analysis of the experimental findings examines the total length, obstacle recognition, and efficiency improvement achieved by this method. The experimental findings demonstrated that the proposed method outperforms standard methods in terms of accuracy and efficiency in path planning.
Keywords: SLAM, Deep vision computing, Robot path planning, warehouse management, agricultural logistics, agriculture warehouse.

INTRODUCTION

The agricultural logistics warehouse management is encountering growing issues due to the swift advancement of the global logistics business and the emergence of e-commerce (Radácsi *et al.*,2022). The limitations of traditional human resource management in adapting to quickly changing needs have led to an increasing need for automated agricultural logistics warehouse management robots (Gubán M *et al*. 2022 and Huimin and Zhao, 2023; Naji *et al*., 2023). The key concern in managing agricultural logistics warehouse robots is path planning (Mo *et al.*, 2022). The objective is to determine efficient and safe routes for robots to swiftly and accurately handle things within agricultural logistics warehouses (Kabir *et al.*, 2023). Robot path planning is a crucial and intricate matter in the operation of agricultural logistics warehouses (Path, 2018). Optimal path planning can optimize the efficiency of agricultural logistics warehouses and guarantee the prompt and precise delivery of items to their intended locations (Raza and Fernandez, 2015).

Foumani *et al*. (2017) introduced a technique to decrease the duration of partial cycles in these cells across three different inspection situations: during the manufacturing process, after the manufacturing process, and while the process is ongoing. The purpose of this study was to determine if it is technically possible to replace an inspection scenario that occurs during or after a process with an inspection scenario that occurs in real-time while evaluating a simple two-machine robotic rework cell. As inspection application scenarios become more complex and varied, the performance of robots in autonomous navigation is under more demands. The fundamental elements of robot navigation technology consist of path planning

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technology and SLAM technology. Simultaneous Localization and Mapping (SLAM) is the method via which a mobile robot ascertains its precise location and constructs a map by using sensors in its immediate surroundings. Path planning technology utilizes task objectives and specifications to produce an optimal navigation path for the robot to reach the intended location.

The complexity of agricultural logistics warehouse environments and the limitations of robots pose challenges for traditional path planning methods. These include problems such as path conflicts, inefficient path selection, and the inability to adapt to real-time environmental changes. This article proposes a path planning method based on SLAM and deep vision computing to address these issues in agricultural logistics warehouse management robots. By effectively combining SLAM technology and depth vision computing, we aim to enhance the robots' perception of the environment, accurately recognize objects, and update the environment map in real-time. This approach is expected to provide robots with more accurate and efficient path planning results. The research process is illustrated in Fig. 1.

This article provides a detailed introduction to the principle and implementation process of path-planning method. The study designs and implements a path planning algorithm that comprehensively considers robot perception ability, path conflict avoidance, and path selection optimization based on the specific situation of agricultural logistics warehouse management. At the same time, it verifies and evaluates path-planning methods based on actual data and simulation experiments to verify their feasibility and effectiveness in agricultural logistics warehouse scenarios. New solutions and methods for path planning to resolve the problem of agricultural logistics warehouse management robots can be achieved by optimizing the path planning algorithm, which has the potential to improve the efficiency of agricultural logistics warehouse management, reduce costs, and make a certain contribution to the development of the logistics industry. Main contributions of this paper are summed up as follows:

1) This study combines deep vision computing to further enhance the perception and understanding ability of robots by analyzing and identifying information such as objects, roads, and obstacles in the warehouse environment, thus enabling more accurate path planning.

2) We combine deep learning and planning algorithms to propose an efficient path planning algorithm through comprehensive analysis of warehouse environment and transportation needs.

3) The contribution of this research topic is to propose a path planning method for agricultural logistics warehouse management robots based on SLAM and deep vision computing, which combines key technologies such as perception, positioning, map construction, and path planning to improve the accuracy and efficiency of robot path planning. It has broad application prospects and practical significance.

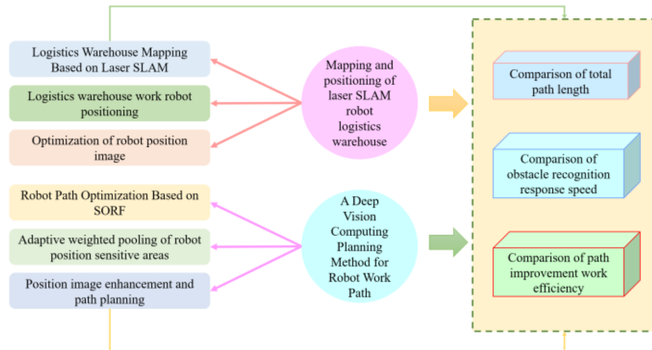

Figure 1. Research flowchart

MATERIALS AND METHODS

***Agricultural logistics warehouse Mapping Based on Laser SLAM*:** The path planning of agricultural logistics warehouse management robots is one of the hot research directions in the modern logistics field. Among them, agricultural logistics warehouse mapping based on Laser SLAM (Simultaneous Localization and Mapping) is one of the fundamental steps in path planning (Vinod and Saikrishna, 2022). Laser SLAM is a technology that obtains environmental information through laser sensors and simultaneously achieves autonomous positioning and map construction. In agricultural logistics warehouses, laser SLAM can scan the surrounding environment through laser sensors and generate real-time warehouse maps based on the scanning data (Liu *et al.*, 2021). This map contains various objects and structural elements of the warehouse, such as shelves, obstacles, doors, etc. With the help of laser SLAM, agricultural logistics warehouse management robots can achieve autonomous navigation and obstacle avoidance in unknown environments (Gui, 2023). In agricultural logistics warehouse mapping, the first step is to select a suitable laser sensor and install it on the robot. Then, the robot will move within the warehouse and continuously obtain measurement data of objects and the environment through laser sensors. These data can include information such as the position, shape, and size of objects, as well as structural information within the warehouse (Liu *et al.*, 2021). Due to the potential mutual constraints between simultaneous localization and mapping during simultaneous computation, the localization part of the RBPF SLAM problem uses the RBPF particle filter algorithm to estimate the robot's pose state, while the map construction part uses the Extended Kalman Filter (EKF) algorithm to estimate the pose state. The problem is described as calculating the robot's pose estimation set $x_{1:K}$ and the map estimation set m. The positioning and mapping process is expressed as follows:

$$p(x_{1:k},m|z_{1:k},u_{1:k-1})=p(x_{1:k}|z_{1:k},u_{1:k-1})p(m|x_{1:k},z_{1:k}) \quad (1)$$

where $x_{1:t}=[x_1,...x_k]$ represents the current pose set of k positions. $p(x_{1:k},|z_{1:k},u_{1:k-1})$ represents the prior probability estimation of the robot's pose, and $p(m|x_{1:k},z_{1:k})$ represents the update of the global map.

The SLAM problem is to calculate the pose set $x_{1:K}$ and the feature position estimation set m, which requires estimating the pose of the robot k consecutive times based on the robot's control input $u_{1:k}$ and observation sequence $z_{1:k}$. The subgraph matching process can be seen as solving a nonlinear least squares problem:

$$\underset{\zeta}{argmin} \sum_{k=1}^{k} \left(1-M_{smooth}(T_\zeta h_k)\right)^2 \quad (2)$$

In the formula, $T_\zeta h_k$ represents the global coordinates of radar information after a coordinate transformation, while M_{smooth} represents a bicubic interpolation function (Kalinov *et al.*, 2020).

The choice of heuristic function $h(n)$ affects the effectiveness of path planning, so choosing a suitable heuristic function is crucial for the performance of autonomous navigation. For map search, we usually choose Manhattan distance or Euclidean distance as the heuristic function throughout the entire search process.

$$h_e(n)=\sqrt{(a_x-b_x)^2+\left(a_y-b_y\right)^2} \quad (3)$$

$$\underset{\zeta}{argmin} \sum_{k=1}^{k} \left(1-M_{smooth}(T_\zeta h_k)\right)^2 \quad (4)$$

In the above equation, $h_e(n)$ represents the Euclidean distance, $h_m(n)$ represents the Manhattan distance, a_{xh} and b_x represent the horizontal and vertical coordinates of node a, and b_x and by represent the horizontal and vertical coordinates of node b, respectively. Place all the searched grids in two sets, namely the searched and unsearched sets, and update the path information after all the unsearched sets are searched. The diagram construction process is shown in Fig. 2. In path planning, the established warehouse map can be used to select the optimal path for robots through path planning algorithms, in order to achieve efficient logistics transportation. The goal of path planning is usually to minimize the robot's travel distance, reduce obstacle avoidance times, and optimize warehouse resource utilization.

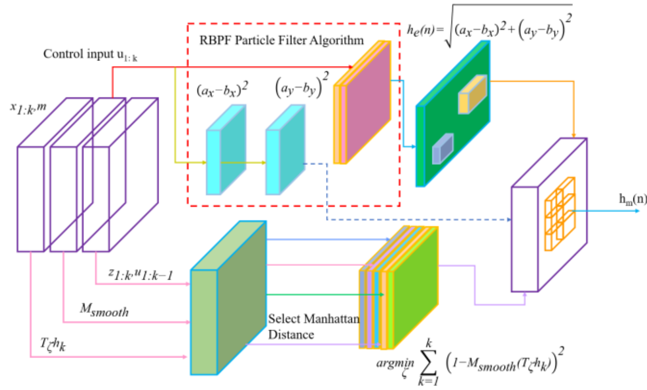

Figure 2. SLAM Agricultural logistics warehouse Map Construction.

***Agricultural logistics warehouse work robot positioning*:** Deep vision computing refers to the use of deep learning models and computer vision technology to perceive and understand the environment (Konstantinidis *et al.*, 2022). In agricultural logistics warehouses, deep vision computing can help robots perceive and recognize key objects such as shelves, goods, and obstacles in real-time, and obtain their position and posture information in three-dimensional space (Lambrecht and Funk, 2020). This information, combined with the results of SLAM positioning, can more accurately determine the position of the robot. Robots use sensors such as LiDAR and cameras to obtain data on the surrounding environment, and use deep learning models for object detection, recognition, and pose estimation to obtain position information of objects such as shelves, goods, and obstacles (Wang *et al.*, 2021). Then, the SLAM algorithm is used to process the perceived environmental data, construct a map, and estimate its own location. SLAM can accurately match the robot's position with the environmental map, thereby achieving accurate positioning. The obstacle labels along the robot's path are shown in Table 1.

For the external feature information observed by LiDAR, it is necessary to establish an observation model for description and analysis. This article describes the observation of LiDAR in polar coordinates, mainly including the direction and position information between LiDAR and environmental features. The expression form is as follows:

$$z_t^i=(\rho_t^i,\varphi_t^i)^T \quad (5)$$

In the formula, z_t^i represents the observation of the i feature point in the environment at time t. ρ_t^i represents the geometric distance between the i feature point in the environment at time t and the LiDAR. Assuming the global pose of the mobile robot at time t is $(x_t,y_t,\theta_t)^T$, and the robot observes several landmark features through LiDAR, where the position of the i feature is (x_t^i,y_t^i). Therefore, the LiDAR observation model can be represented as:

$$Z(t)=\begin{bmatrix}\rho_t^i\\ \varphi_i^i\end{bmatrix}=\begin{bmatrix}\sqrt{(x_t^i\text{-}x_t)^2+\left(y_t^i\text{-}y_t\right)^2}\\ arctan(\frac{y_t^i\text{-}y_t}{x_t^i\text{-}x_t})\end{bmatrix}+v(t),i=1,2,\cdots,N \qquad (6)$$

In the formula, *Z(t)* represents the observed landmark features of the LSTM LiDAR at time t, and *v(t)* represents the observation noise of the system. The observation model based on LiDAR describes the relationship between robots and environmental features from a mathematical perspective, abstracting it into a universal observation equation, which is expressed as follows:

$$Z(t)=h(S(t),v(t)) \qquad (7)$$

Based on the current and target positions of the robot, use path planning algorithms to calculate the optimal path that the robot needs to follow. The path planning algorithm takes into account factors such as obstacles and shelf layout in the environment to ensure that the robot can safely reach the target position. Positioning and path planning need to be updated in real-time during robot motion. By continuously perceiving and locating, robots can timely correct their own positions and re plan their paths based on the latest environmental information to cope with environmental changes and avoid obstacles.

Table 1. Path Obstacle Labels.

Tags	Function and Description
<robot>	Name and its partial attributes
<link>	The appearance and physical properties of a rigid body
<joint>	Joint kinematics and dynamic properties
<visual>	Describe the appearance label of the robot
<collsion>	Describe the collision properties of the link
<inertial>	Describe robot inertia labels

Optimization of robot position image: SLAM (simultaneous localization and map construction) and depth vision computing are commonly used technical means in robot navigation and path planning. Robot path planning typically requires precise positional information, and machine vision technology can provide this type of information. In agricultural logistics warehouse management, robot path planning needs to consider the available path and location information in the warehouse, as robots need to accurately navigate to designated locations such as material racks, docks, and equipment locations (Roa-Garzón M A *et al*. 2019). Therefore, it is necessary to optimize the robot position image using machine vision technology. Location image optimization can be achieved through the use of deep learning neural networks for image recognition and feature extraction. Convolutional neural networks (CNN) can be used to classify images captured by robots, thereby identifying objects in the warehouse and determining the robot's position. In this way, the robot can obtain accurate position information and perform path planning. The robot's motion position diagram is shown in Fig. 3.

In the graph model of SLAM problem, nodes are represented by C_1, C_2… to represent different observation positions of the camera, P_1, P_2… to represent several map points, and the edges between nodes represent observation constraints. In the graph optimization model, optimize variables for *m* observation positions and *n* map points.

$$x=[\xi_1,\ldots,\xi_m,p_1,\ldots,p_n]^T \qquad (8)$$

In the formula ξ The Lie algebraic form of camera pose, *P* map point coordinates.

$$C=min \sum_{i,j} \rho(e_{i,j}^T\boldsymbol{\Omega}_{i,j}^{-1}\boldsymbol{e}_{i,j}) \qquad (9)$$

In the formula, $e_{i,j}$ is the observation errors between pose *i* and map point *j*, and the specific calculation method depends on the error model selected by the system. ρ a robust kernel function used to suppress the impact of outliers on overall error.

The edge length of the H matrix is directly proportional to the observation position and the number of map points. Due to the fact that the actual number of constraints in the SLAM problem is much smaller than the number of fully connected edges of all nodes, H is a sparse matrix. Expand the equation into different regions of the matrix.

$$\begin{pmatrix}B & E\\ E^T & C\end{pmatrix}\begin{pmatrix}\Delta x_c\\ \Delta x_p\end{pmatrix}=\begin{pmatrix}v\\ w\end{pmatrix} \qquad (10)$$

In the formula, *B* is only related to the camera pose, and *C* is only related to the coordinates of map points. Due to the fact that the number of observed map points is much greater than the number of their own poses, the size of *C* is much larger than that of *B*. When there are no constraints between cameras or map point coordinates, *B* and *C* are both diagonal block matrices. Using marginalization to transform the equation into:

$$(B\text{-}EC^{-1}E^{\uparrow})\Delta x_c=v\text{-}EC^{-1}w \qquad (11)$$

Robot path planning based on visual SLAM technology can merge the robot's visual data and LiDAR scanning data to achieve robot positioning and map construction. This method not only makes robot path planning more accurate, but also can cope with changes and movements of objects in the warehouse. The position image optimization combining SLAM and depth vision computing is an important method for achieving robot path planning. Robots can accurately determine their position using visual data, and then use path planning algorithms to plan the optimal path, improving the efficiency and accuracy of agricultural logistics warehouse management.

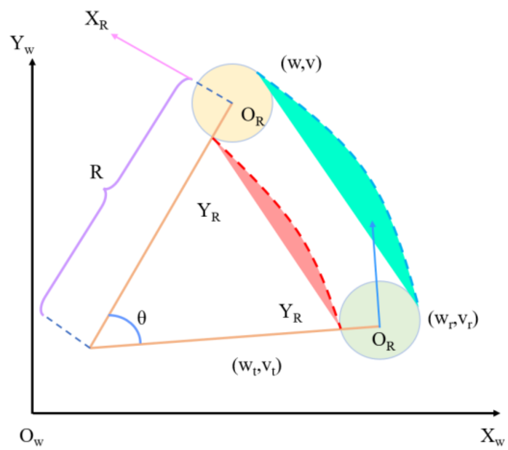

Figure 3. Schematic diagram of robot motion position.

***Robot Path Optimization Based on SORF*:** Robot path optimization based on SORF (Semantic Object Recognition and Fusion) is a comprehensive solution that integrates multiple technologies. Firstly, using SLAM technology, robots obtain environmental information through sensors and construct maps in real-time. Then, deep learning techniques can be used for semantic object recognition to mark different recognized objects in the map, such as shelves, obstacles, etc. In this way, robots can perceive and recognize various elements in the environment. In the visual system, ganglion cells and LGN neurons have the same receptive field and color antagonism mechanism, generally referred to as the subcortical layer. After receiving color signals from retinal cone cells, neurons in this layer exhibit a single antagonistic output response, which can usually be simulated using the double Gaussian difference function shown in the following equation.

$$Gau(x,y)=\frac{1}{2\pi\sigma^2}exp\left(-\frac{x^2+\gamma^2y^2}{2\sigma^2}\right) \quad (12)$$

$$SO_{C^+/S^-}(x,y)=\big(C(x,y)-k(x,y)\times S(x,y)\big)*Gau(x,y) \quad (13)$$

In the formula $(x,y)=(x\cos\theta+y\sin\theta,-x\sin\theta+y\cos\theta)$.$\sigma$ and γ Represent the scale parameters and ellipticity of SORF, respectively. $C(x,y)$ and $S(x,y)$ represent four color components of cone cells, namely red, green, blue, and yellow (R, G, B, Y), and the four color antagonistic channels

Brightness and color are the criteria for determining image boundaries, while cone cells have different sensitivities to both under different light intensities, which prevents them from simultaneously participating in the encoding response of color boundaries. In order to weaken the interference of light intensity on a single antagonistic response, the brightness component L (x, y) of the input image I (x, y) is first obtained, and the average brightness Lavg (x, y) in the H * H region is calculated with each pixel point as the center.

$$(B-EC^{-1}E^{\uparrow})\Delta x_c=v-EC^{-1}w \quad (14)$$

The bilateral visual pathway is not completely independent and parallel, but there are many horizontal channels for interactive integration of visual information. Utilize the different functions of the dorsal and ventral attention pathways to synergistically process visual information through interactive mechanisms. The purpose of doing this is to enhance the prominent contours and weaken the texture background, in order to achieve better visual effects. Through the interaction of this bilateral attention pathway, the model can better process visual information, making the target more prominent and the background more blurred. This visual information interaction response model is expected to play an important role in fields such as visual processing and image recognition.

In the path planning stage, robots can optimize their paths based on semantic object information on the map. SORF technology can classify and analyze different objects in the environment, and then construct semantic relationship graphs of objects. On this basis, robots can use graph theory algorithms, such as the shortest path algorithm, to transform the path planning problem into a problem of finding the optimal path on the semantic relationship graph. By selecting appropriate path planning algorithms and considering real-time environmental information, robots can plan paths more intelligently, avoid obstacles, and reach target positions more quickly.

Adaptive weighted pooling of robot position sensitive areas: In deep learning, pooling is a downsampling operation commonly used to reduce the spatial dimension of feature maps (Cong *et al.*, 2021). In the path planning of agricultural logistics warehouse management robots, we can divide the environment into multiple areas and then perform pooling operations on each area to obtain a feature representation of that area. However, different regions have varying degrees of sensitivity to the robot's position. For example, the area around the robot has a greater impact on its position estimation, so higher weights should be given. The area further away from the robot has a smaller impact on its position estimation and should be given a lower weight.

Although the text suggestion box generation sub network can recall almost all text instances, it contains false positive detection results for many types of text, resulting in a relatively low accuracy. Similarly, we have adopted a strategy of further refining the suggested candidate boxes for the text regions output in the first stage. Using the output of the last convolutional layer of the above hyper feature generation module, generate a score map of k^2 channels for each category, and pool the corresponding pixels in the (i,j) grid to obtain it.

$$r_c(i,j|\Theta)=\sum_{(x,y)\in bin(i,j)}\frac{z_{i,j,c}(x+x_0,y+y_0|\Theta)}{n} \quad (15)$$

In the formula, $r_c(i,j|\Theta)$. It is the pooling value of the (i,j) grid of category c, where $z_{i,j},c$ represents a fraction plot from $k^2(C+1)$, (x_0, y_0) represents the upper left corner coordinate value of a region of interest (RoI), and n represents the number of pixels in the (i, j) grid. Θ Represents all network weight parameters. After the pooling process of position sensitive regions of interest, global pooling is performed on k^2 score sensitive feature maps.

$$r_c(\Theta)=\sum\frac{r_c(i,j|\Theta)}{k^2} \quad (16)$$

Throughout the entire training process, we adopt a similar multi task learning approach to optimize the generation of text region suggestion candidate boxes, and further utilize text hyperfeatures to refine each text suggestion candidate box. The above is an adaptive weighted pooling method for robot position sensitive areas used in research (Radácsi *et al.*, 2022). The method calculates the distance between each area and the robot position based on the current position of the robot, and then uses the distance as a weight for weighted pooling. The closer the region is, the higher the weight, and the greater the contribution of the corresponding feature representation in the pooling result (Singh *et al.*, 2022). The farther away the area is, the lower the weight, and the smaller the contribution of the corresponding feature representation in the pooling result. By using an adaptive weighted pooling method for robot position sensitive areas, the accuracy of robot path planning can be improved while maintaining the high-dimensional feature representation of the pooling results.

***Position image enhancement and path planning*:** Position image enhancement refers to the use of deep vision computing technology to process and optimize images in agricultural logistics warehouses, thereby enhancing the robot's position perception and navigation capabilities. Path planning refers to how to effectively plan the path of robots in agricultural logistics warehouses so that they can efficiently complete tasks. In agricultural logistics warehouse management, robots need to accurately perceive their position in the warehouse environment in order to plan their paths correctly and avoid collisions. Traditional SLAM technology integrates sensor data such as LiDAR for localization and mapping, but it may have limitations in certain complex scenarios. Therefore, the introduction of deep vision computing technology can effectively improve the accuracy of localization. Deep vision computing technology mainly utilizes cameras to obtain image information, and uses deep learning algorithms to recognize, analyze, and process images. In agricultural logistics warehouses, scene images around robots are obtained through cameras, and deep learning algorithms are used to extract features and recognize images, thereby obtaining accurate information about the robot's location.

Natural images have extremely high structure, and there is a strong correlation between the pixels of the images. Structural similarity is measured by detecting whether the structural information has changed to measure the similarity between two images. The closer the values of structural similarity are, the formula for calculating structural similarity is:

$$SSIM=\frac{(2\mu_x\mu_y+c_1)(2\sigma_{xy}+c_2)}{(\mu_x^2+\mu_y^2+c_1)(\sigma_x^2+\sigma_y^2+c_2)} \quad (17)$$

Among μ_x, μ_y represents the average value of two images σ_{xy} represents the covariance of two images, σ_x^2 and σ_y^2 "respectively represent the variance of two images, and c_1 and c_2 are constants used to maintain computational stability. The peak signal-to-noise ratio compares the strength of the required signal with the strength of background noise. The higher the peak signal-to-noise ratio, the smaller the distortion of the processed image.

$$PSNR=10\times log_{10}\left(\frac{(2^n-1)^2}{MSE}\right) \quad (18)$$

$$MSE=\frac{1}{H\times W}\times\sum_{i=1}^{H}\sum_{j=1}^{W}(X(i,j)-Y(i,j))^2 \quad (19)$$

Among them, MSE represents the mean square error of two images, H represents the height of the image, W represents the width of the image, and n is the number of bits required to store each pixel's pixel value. The research pseudocode is shown in Table 2.

In terms of path planning, combining position image enhancement information can more accurately plan the path of robots in agricultural logistics warehouses. The goal of path planning is to enable robots to efficiently complete tasks while avoiding collisions with other objects or obstacles. The position image enhancement based on SLAM and depth vision computing can provide more accurate position information, thereby enabling more precise planning of the robot's movement path. The study presents the traditional path selection of an agricultural logistics warehouse and the path selection of the method provided in this study, as shown in Fig. 4.

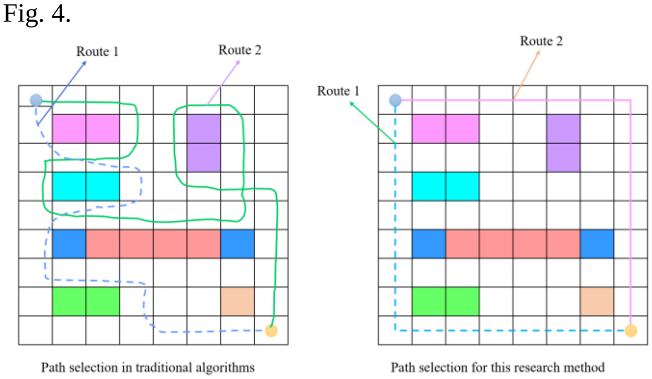

Figure 4. Schematic diagram of robot path selection.

Table 2. Algorithm for Path Planning Method for Agricultural logistics warehouse Management

Algorithm 1: SLAM and Deep Vision Computing-based Robotic Path Planning Method for Agricultural logistics warehouse Management	
1：	Input: Map estimation set *m*, Manhattan distance $h_m(n)$, Euclidean distance $h_e(n)$, observed landmark features $Z(t)$ by LSTM LiDAR at time t, and system observation noise $v(t)$.
2：	Using Extended Kalman Filter (EKF) algorithm for estimation
3：	$1\text{-}M_{smooth}(T_\zeta h_k)$
4：	**for all** *i* =1 to N **do**

$(x_t$ ^i $-x_t)$^2+$(y_t$^i-$y_t)$^2
Latest environmental information, re planning path
$Z(t)=h(S(t),v(t))$
Optimize variables for m observation positions and n map points
for k 1 : t
$k(x,y)\times S(x,y)$
$(x,y)=(x\cos\theta+y\sin\theta,-x\sin\theta+y\cos\theta)$
if Interference of Light Intensity on Single Antagonistic Response
Pooling of pixels at corresponding positions
else
Computed position image enhancement
end for
end for

RESULTS

Comparison of total path length**:** By comparing the total length of paths, we can evaluate the effectiveness and performance of different path planning methods. A shorter total path length means that the robot can reach its destination faster during task execution, reducing movement time and cost. Real time environmental maps of agricultural logistics warehouses are established using SLAM technology, and obstacles in the environment are identified and located using deep vision computing technology. Accurate environmental modeling and perception can help robots choose the optimal path to avoid obstacles. Use appropriate path planning algorithms to generate the optimal path. Based on these constraints, path planning can be further optimized to enable the robot to complete tasks within a given time and minimize the total length of the path, as shown in Fig. 5.

The average ratio of the total length of the FPGA algorithm's route to the traditional route is 97.67, indicating that compared to the traditional route, the FPGA algorithm can reduce the total length of the route by about 2.33%, with a high degree of optimization. The average ratio of the total length of the ROS algorithm's route to the traditional route is 99.92, indicating that compared to the traditional route, the ROS algorithm can reduce the total length of the route by about 0.08%, with a higher degree of optimization. However, compared to other algorithms, the degree of optimization is lower. The average ratio of the total length of the Dijkstra algorithm's route to the total length of the traditional route is 103.67, indicating that compared to the traditional route, the total length of the route obtained by the Dijkstra algorithm is slightly higher, indicating a lower degree of optimization.

The average ratio of the total length of the genetic algorithm route to the total length of the traditional route is 93.67, indicating that compared to the traditional route, the genetic algorithm can reduce the total length of the route by about 6.33%, with a high degree of optimization. The average ratio of the route length of this study algorithm to the total length of traditional routes is 87.14, indicating that compared to traditional routes, this study algorithm can reduce the total length of routes by about 12.86%, with the highest degree of optimization. In summary, this study algorithm has the highest degree of optimization. In order to understand which interval or intervals each method will appear in roughly, we calculated its distribution interval based on the above results as shown in Fig. 6.

The FPGA algorithm performs well overall with a ratio range of 78 to 118. A small ratio indicates a high degree of route optimization, especially in the 10th data. The ratio range of ROS algorithm is between 90 and 119, and its performance is relatively poor. A larger ratio indicates a relatively low degree of route optimization, especially in the third, sixth, and seventh data points. Dijkstra algorithm: Its ratio range is between 83 and 123, and the overall performance is good. A small ratio indicates a high degree of route optimization, especially in the 11th and 12th data. Genetic Algorithm algorithm: Its ratio range is between 74 and 104, and overall performance is good. A small ratio indicates a high degree of route optimization, especially in the 9th and 10th data. This study algorithm: Its ratio range is between 61.58 and 150.26, with the best overall performance. The minimum ratio indicates that the algorithm has the highest degree of optimization for the route. Overall, this study algorithm exhibits the best optimization degree in the vast majority of cases, with the smallest ratio among all data, indicating that the algorithm has the highest degree of optimization for the route.

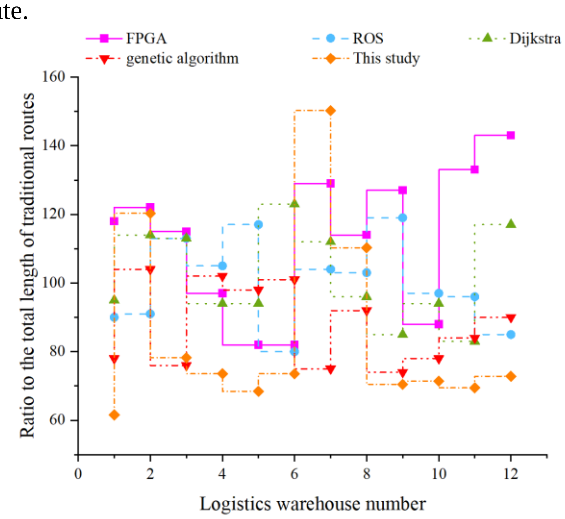

Figure 5. Total path length result

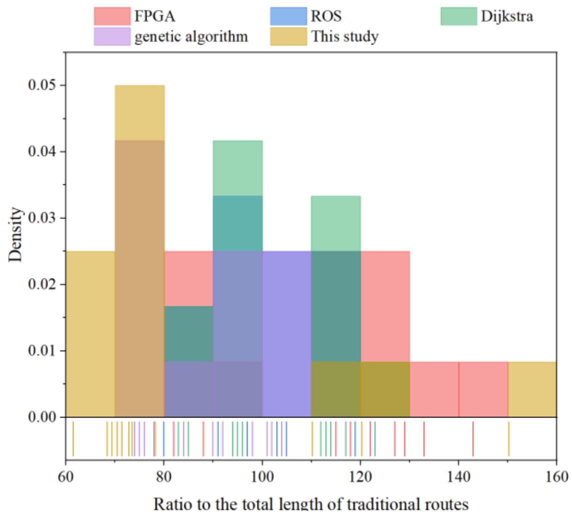

Figure 6. Display the interval of total length

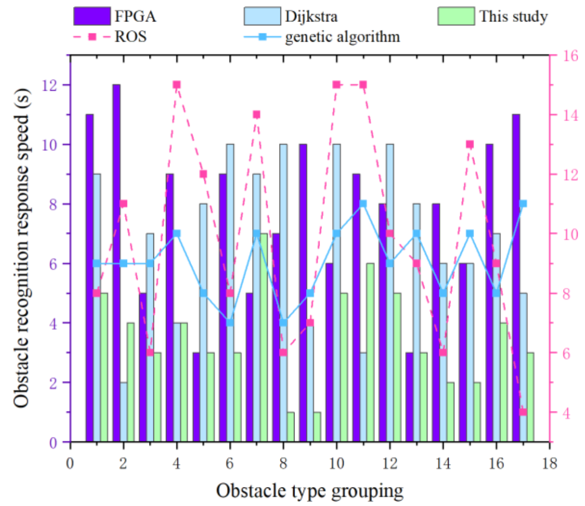

Figure 7. Result of obstacle recognition response speed

***Comparison of obstacle recognition response speed*:** The response speed of obstacle recognition is a crucial indicator in the path planning of agricultural logistics warehouse management robots. It determines how quickly a robot can recognize and take corresponding actions when encountering obstacles in the environment. In agricultural logistics warehouse management robots based on SLAM (Simultaneous Localization and Mapping) and deep vision computing, obstacle recognition mainly relies on the processing ability of sensor data and algorithms.

Common sensors include cameras, LiDAR, etc., which can sense the environment around robots and transmit the perceived information to algorithms for processing. Analyze the comparison of obstacle recognition response speed from the characteristics of sensors, algorithm design, and computing power. The design and optimization of algorithms also have a significant impact on the response speed of obstacle recognition. Image processing algorithms based on deep learning can quickly and accurately identify obstacles. The real-time performance of the SLAM algorithm and the accuracy of environmental mapping are also key factors. By selecting appropriate algorithms and combining them with the performance of hardware devices, the response speed of obstacle recognition can be improved, as shown in Fig. 7 and 8.

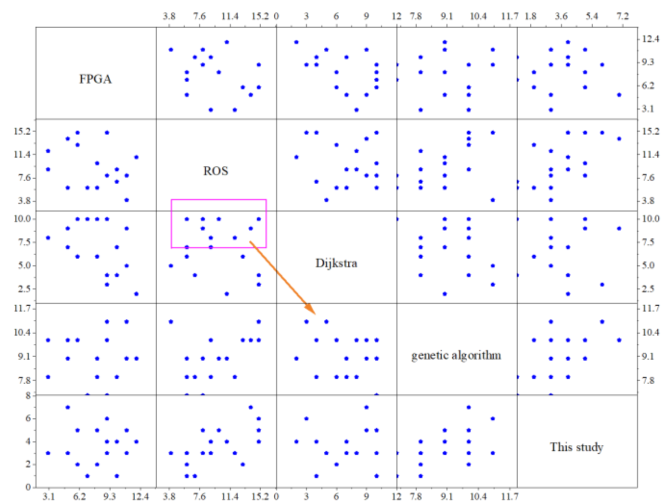

Figure 8. Matrix response analysis

The average response time of FPGA algorithm is 8.35 seconds, ROS algorithm is 10.18 seconds, Dijkstra algorithm is 7.53 seconds, Genetic algorithm is 9.07 seconds, and This study algorithm is 3.47 seconds. From the perspective of average response time, this study algorithm has the shortest response time, ROS algorithm has the longest response time, and other algorithms are in the middle. We can observe the minimum and maximum response times and their range of variation for each algorithm. The minimum response time of the FPGA algorithm is 3 seconds, the maximum response time is 12 seconds, and the range of variation is 9 seconds. ROS algorithm: The minimum response time is 4 seconds, the maximum response time is 15 seconds, and the range of variation is 11 seconds. Dijkstra algorithm: The minimum response time is 2 seconds, the maximum response time is 10 seconds, and the range of variation is 8 seconds. Genetic algorithm: The minimum response time is 7 seconds, the maximum response time is 11 seconds, and the range of variation is 4 seconds. This study algorithm: The minimum response time is 1 second, the maximum response time is 7 seconds, and the range of variation is 6 seconds. According to the average response time, obstacle type group 5 has the shortest response time, obstacle type group 2 has the longest response time, and the response time of other groups is in the middle.

***Comparison of path improvement work efficiency*:** Path planning has a significant impact on the efficiency of agricultural logistics warehouse management robots. Path planning refers to the process of finding the optimal path or subset for robots or other autonomous mobile systems. In agricultural logistics warehouse management, robots need to autonomously navigate the environment and complete cargo handling tasks. The goal of path planning is to enable robots to efficiently complete tasks, reduce handling time and energy consumption. The integration of SLAM and deep vision computing is widely used in the path planning of agricultural logistics warehouse management robots. This method can achieve high accuracy and real-time positioning ability, providing efficient intelligent warehouse management services. Through this path planning method, agricultural logistics warehouses can achieve automatic collaboration and coordination of tasks among multiple robots, thereby achieving smooth task execution.

The results in Fig. 9 show that the average performance range of the FPGA algorithm is between 60 and 68, with relatively small fluctuations. The average performance range of the ROS algorithm is between 60 and 72, with overall fluctuations but an upward trend. The average performance range of Dijkstra algorithm is between 67 and 82, with some fluctuations, but overall it shows a downward trend. The average performance range of the genetic algorithm is between 60 and 80, with small fluctuations. The average performance range of this study algorithm is between 71 and 84, with small fluctuations and an overall upward trend. The Dijkstra algorithm has the highest average efficiency, but there are significant fluctuations under different warehouse planning times.

The average efficiency of the ROS algorithm is gradually improving and may have potential advantages in large-scale warehouse planning. The performance of the genetic algorithm is relatively stable, but the overall efficiency is low. This study algorithm performs the best in improving work efficiency and has a relatively stable advantage under different warehouse planning times. This study algorithm has the best effect on improving work efficiency. Compared with traditional path planning methods, methods based on SLAM and deep vision computing have improved warehouse operation efficiency. The methods based on SLAM and deep vision computing can enable robots to respond promptly to changes in the environment and maintain highly accurate path planning by constructing real-time environmental maps and continuously optimizing paths.

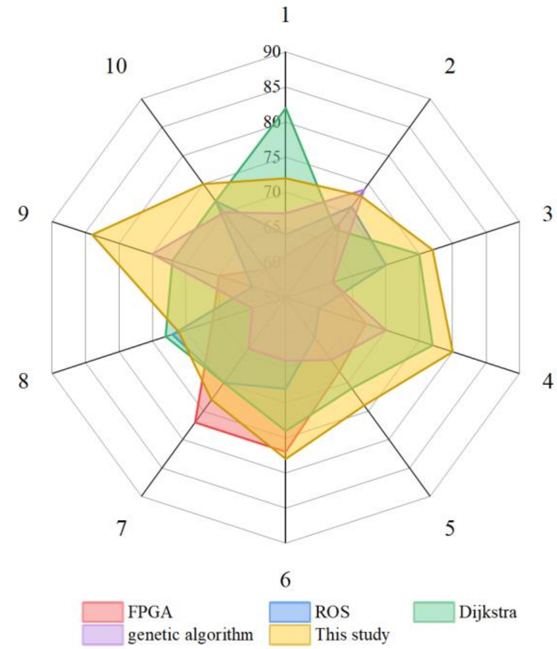

Figure 9. Comparison of path improvement work efficiency

DISSCUSION

SLAM (Simultaneous Localization and Mapping) is one of the common problems in the field of robotics, which involves the ability of robots to simultaneously perceive and establish environmental maps as well as self-localization. SLAM technology can help robots perceive various obstacles in the environment (including pedestrians, walls, furniture, etc.), which is crucial for the path planning of agricultural logistics warehouse management robots. Therefore, many researchers at home and abroad have conducted relevant research based on SLAM and deep vision computing to improve the accuracy and efficiency of agricultural logistics warehouse management robots.

Han (2023) proposed a multi-sensor fusion scheme based on visual odometry and IMU (Inertial Measurement Unit) sensors to improve the localization and path planning capabilities of autonomous mobile robots. KenK et al. (2019) conducted a research on path planning for semi autonomous mobile robots based on SLAM technology. The system used LiDAR and RGB-D cameras for 3D environment modeling to achieve autonomous navigation of semi autonomous mobile robots. The research team at Northwestern Polytechnical University proposed a 3D point cloud semantic segmentation algorithm based on deep learning and applied it to the path planning of semi-autonomous agricultural logistics warehouse robots. Gao et al. (2018) were committed to developing various algorithms and systems to improve the map construction and localization capabilities of warehouse robots. For example, map building algorithms based on LiDAR or depth cameras use techniques such as filters, optimization, and machine learning to construct warehouse maps and locate robots in real-time and accurately.

Parikh et al. (2022) trained convolutional neural networks to detect and recognize goods in warehouses, helping robots correctly identify and locate goods without human intervention. Bernardo et al. (2022) provideda solution for task collaboration among multiple robots by developing intelligent distributed scheduling algorithms and communication protocols. Asadi et al. (2018) focused on applying their research findings to practical agricultural logistics warehouses and integrating and optimizing the entire system. They developed new hardware and software platforms to achieve autonomous navigation, path planning, and cargo handling capabilities of robots. By integrating with existing warehouse management systems, researchers can ensure good collaboration between robots, human operators, and other devices, and achieve warehouse automation and efficiency in practical environments.

The above aspects have been deeply studied and explored in domestic and international research. Through the promotion of these research results, the path planning method for agricultural logistics warehouse management robots based on SLAM and deep vision computing is expected to significantly improve the automation level and work efficiency of warehouses.

This study focused on the path planning method for agricultural logistics warehouse management robots based on SLAM and deep vision computing, aiming to provide an intelligent and efficient path planning method to optimize the operation effect of agricultural logistics warehouse management robots. We have successfully applied SLAM technology and deep vision computing technology to construct the environmental map and perception ability of agricultural logistics warehouse management robots. SLAM technology can obtain real-time information on the position of robots in warehouses and the surrounding environment, while deep vision computing technology can provide accurate and fast object recognition and positioning capabilities. The combination of these two technologies provides us with comprehensive environmental cognitive abilities, laying the foundation for path planning. We adopted a path planning method based on heuristic algorithms, combining the dynamic environment perception and motion ability of robots. By dynamically updating map information and perceiving obstacles in the environment in real-time, robots can plan their paths based on the latest information and adjust their paths in a timely manner when encountering obstacles or other changes. At the same time, we also considered the motion ability of the robot, optimizing the length and time of the path to enable the robot to reach the target position as soon as possible while ensuring safety.

This study successfully proposed and validated a path planning method for agricultural logistics warehouse management robots based on SLAM and deep vision computing. This method can effectively improve the efficiency and accuracy of robot path planning, providing an intelligent solution for agricultural logistics warehouse management. Future research can further optimize path planning algorithms, enhance the adaptability of robots to complex environments, explore more application scenarios, and promote the development of agricultural logistics warehouse management robot technology.

Conclusion: SLAM (Simultaneous Localization and Mapping) is a crucial problem in robotics, enabling robots to perceive and establish environmental maps. Researchers have developed various methods to improve the accuracy and efficiency of agricultural logistics warehouse management robots. These methods include multi-sensor fusion schemes, LiDAR and RGB-D cameras, deep learning algorithms, and convolutional neural networks. This study focuses on a path planning method for these robots based on SLAM and deep vision computing, aiming to optimize their operation and improve automation. The method combines real-time environmental information with heuristic algorithms, allowing robots to plan their paths based on the latest information and adjust their paths accordingly. Future research should focus on optimizing path planning algorithms and exploring more application scenarios.

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