



Path planning and real time positioning algorithm of intelligent robot based on cloud computing

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Received: 23 May 2021 / Revised: 16 July 2021 / Accepted: 27 July 2021 / Published online: 4 January 2022

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Abstract As a special method to solve nonlinear problems, intelligent computing is attracting people's attention. It is a discipline that uses computational means or methods to acquire and express knowledge and simulate intelligent behavior. Path planning is an important direction of mobile robot research. As one of the basic links of autonomous mobile robot navigation, it seeks the optimal or nearly optimal collision-free path from the initial state to the target state. This article mainly uses intelligent calculation methods to study the path planning algorithm for mobile machines. In order to improve the ability of robots to perform tasks in complex environments, this paper introduces the back-end infrastructure. Grid method, artificial potential field method and ant colony algorithm are all research methods in this paper. Established a cloud computing-based robot intelligent path planning and real-time positioning algorithm research model, researched the cloud computing platform-based robot path planning and real-time positioning algorithm. On the basis of comparing the advantages and disadvantages of these algorithms, the related deficiencies and reasons are analyzed, and the algorithm is improved by using rough set theory. Completed the robot path planning and real-time positioning algorithm based on cloud computing, and realized obstacle avoidance and movement in the unknown static obstacle environment. Complete the overall and partial path

planning tasks of the robot system. The introduction of cloud computing systems has improved the efficiency of overall planning, the results show that the overall path planning efficiency of the intelligent mobile robot is increased by 20%, and the performance of real-time positioning is also increased by 11%. This method has certain practical value.

Keywords Cloud computing · Robot path planning · Real-time positioning algorithm · Robot navigation

1 Introduction

1.1 Background and significance of path planning for cloud computing intelligent robot

Intelligent robot technology is a very broad field of advanced disciplines, which involves the common research and interactive development of many disciplines. These disciplines include control, kinematics, dynamics, sensing technology, planning systems, computer science, and artificial intelligence. Path planning plays an important role in robot technology, so it has become an inevitable trend for experts and scholars at home and abroad to study path planning. The speed of light development of robot technology not only changes the traditional industrial production, but also has a profound impact on human life and entertainment in the foreseeable future. Many countries in the world attach great importance to the development of robot path planning technology and its application in industrial production and human life. Some researchers have studied the operation mechanism of evolutionary algorithm, and proved that the general genetic algorithm

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does not necessarily converge, only when each generation saves the optimal individual. In practical application, the above conclusions are used to ensure the convergence. The best method of individual protection is to introduce the best individuals in each generation directly into the offspring, keeping the population size unchanged, and correspondingly weed out the least adaptable individuals in the offspring.

1.2 Path planning related work of cloud computing intelligent robot

In the planning process, according to the direction change of dynamic obstacles, Huang puts forward corresponding collision avoidance strategies (Qu et al. 2015). Hwu introduces a path planning algorithm for outdoor robot based on neural spike timing (Hwu et al. 2018; Arora et al. 2021). This method is difficult to operate and only stays at the theoretical stage. Fakoor uses fuzzy artificial potential (FAP) method to study two different path planning methods of humanoid robot in unknown environment. Fakoor verified the effectiveness of the two trajectory design methods through hardware and software in the loop simulation (Fakoor et al. 2016). However, the research did not use cloud computing technology, which made the research data insufficient and the research content insufficient. In this method, humanoid robot lacks distance sensor, and traditional artificial potential field method has many limitations.

Aiming at the problem of robot dynamic path planning in complex environment, Xiaofeng proposed a hybrid planning method combining improved ant colony algorithm and Morphine algorithm. The model was established by grid method. The improved ant colony algorithm introduces the inflection point parameters to evaluate the path, so as to process the corner of the path and change the update mechanism of the corner pheromone. Morphine algorithm uses adjacent grid to deal with it to adapt to the grid environment (Xiaofeng et al. 2015). This method is difficult to operate and not practical. Lin proposes an improved population initialization method based on bi-directional fast exploring random tree (birrt) to improve the performance of flexible robot path planning (gacrpp) based on Genetic Algorithm in complex dynamic environment (Lin et al. 2017). This method has a large amount of calculation, needs a lot of data calculation, and has low practicability.

1.3 Innovation of this paper

According to the research results at home and abroad, this paper introduces back-end infrastructure such as cloud computing and big data (Ammar et al. 2016). Grid method,

probabilistic landmark method and ant colony algorithm are used as research methods. On the basis of comparing the advantages and disadvantages of several algorithms, this paper analyzes the related deficiencies and reasons, and improves the algorithms by using rough set theory. Research on the overall path planning, local path planning and real-time positioning algorithm of robots based on cloud computing platform. An online decision-making method is proposed. This method uses the membership function and error cost function with clear physical meaning to adjust the weight of fuzzy neural network. This method is applied to dynamic route planning, and its effectiveness is verified by simulation.

Use the membership function and error cost function with clear physical meaning to adjust the weight of the fuzzy neural network, accelerate the convergence speed of the fuzzy neural network, and give full play to the potential of using artificial neural network and fuzzy inference to solve the robot path planning problem.

2 Research on path planning and real-time positioning algorithm of cloud intelligent robot

2.1 Cloud computing system

Cloud computing is a concept gradually developed after long-term development, the collision and fusion of various ideas and technologies (Cao 2016). From the perspective of service model, cloud computing emphasizes that computing resources are regarded as power and tap water, and users can access and pay according to their usage anytime and anywhere (Serpen and Dou 2015). Enter the huge computing resource pool, and provide corresponding services according to the needs of different levels of cloud users. Cloud computing has many service patterns and a wide range of service objects (Yu 2017). It can flexibly provide a large number of virtual servers for enterprises, so that enterprises can respond to sudden business changes at any time (Wang et al. 2015). It can provide temporary high-performance computing services for scientific research institutions, and avoid the cost of purchasing large amounts of hardware and maintaining basic hardware and software (Hassani et al. 2018; Saudi and Sulaiman 2017).

1. The scale of ultra large scale cloud computing is very large. Google cloud, for example, already has millions of servers in its data centers (Chen et al. 2015).
2. Virtual cloud computing allows users to access all kinds of cloud services anytime, anywhere by using various types of terminals. The various resources that users use are located in a remote cloud, not a specific server in a specific location. Users can use web

browser, mobile phone and other terminals to access the corresponding services through the Internet without knowing the specific location of software services.

3. In some specific cases, general cloud computing is not established. Cloud computing can support various types of software services. Its universality is that different kinds of application services can run on the cloud platform at the same time (Lazarowska 2019; Hasan and Sadiq 2019). The schematic diagram of robot path planning is shown in Fig. 1.
4. The key technologies are mainly applied, including virtualization technology and distributed architecture technology. Server virtualization refers to the virtualization of multiple independent virtual machine servers on the same physical server. It mainly virtualizes hardware resources, supports real-time migration of virtual machines, and reduces cost and system complexity (Tam et al. 2019; Arora and Arora 2020). Completed the robot path planning and real-time positioning algorithm based on cloud computing, and realized obstacle avoidance and movement in the unknown static obstacle environment.

The robot communication induction frame is shown in Fig. 2. Complete the overall and partial path planning tasks of the robot system. The introduction of cloud computing systems has improved the efficiency of overall planning.

2.2 Robot path planning algorithm

In the disabled environment. If the moving object is regarded as a state of the studied problem, the obstacle is regarded as the constraint condition of the problem, and the collision-free path is the solution to the constraint condition, then the spatial path planning is the solution of the multi constraint problem. The objective function is the cost of planning the path, and the constraint condition is to avoid collision with obstacles:

$$\min f(x) x \in R_n, g_i(x) \leq b_i, i = 1, 2, \dots, p \tag{1}$$

$$R_n = [\zeta_1 c_1(t) + \zeta_2 c_2(k) + \zeta_3 c_3(k) + \zeta_4 c_4(k) + \zeta_5 c_5(k) + \zeta_6 w_{ik}] \tag{2}$$

$$\zeta_n c_n(k) = c_1(t) \geq 0, c_2(k) \geq 0, c_3(k) \geq 0 \tag{3}$$

where $f(x)$ is the objective function, $g_i(x)$ is the (nonlinear) constraint condition, and P is the number of constrained inequalities.

In this chapter, the collision risk degree is introduced to describe the collision risk relationship between mobile robot and obstacles, and the collision risk degree is taken as the input of fuzzy neural network controller. This method is simple and easy, but the description is not comprehensive enough. In kinematics, position, velocity and acceleration are closely related. In this paper, it is assumed that the translational velocity and the moving obstacle velocity of the mobile robot are constant in the process of obstacle avoidance.

The robot planning algorithm flow is shown in Fig. 3. The collision risk relationship between mobile robots and obstacles should be related to their distance, relative velocity, and relative acceleration. Where D_i is the distance between the robot and the i th obstacle, VR, B_i are the relative velocity between the robot and the obstacle. A, B is the two most edge points of the obstacle perceived by the sensor on R , and θ is the angle between the relative velocity and the centerline.

The artificial potential field method is a simple and feasible path planning method (Fazlollahatabar 2019; Sangiovanni et al. 2020).

The algorithm is mainly used to control the motion of the robot. With the in-depth research and practice of domestic and foreign scholars, it is found that this method can also be applied to the field of robot path planning:

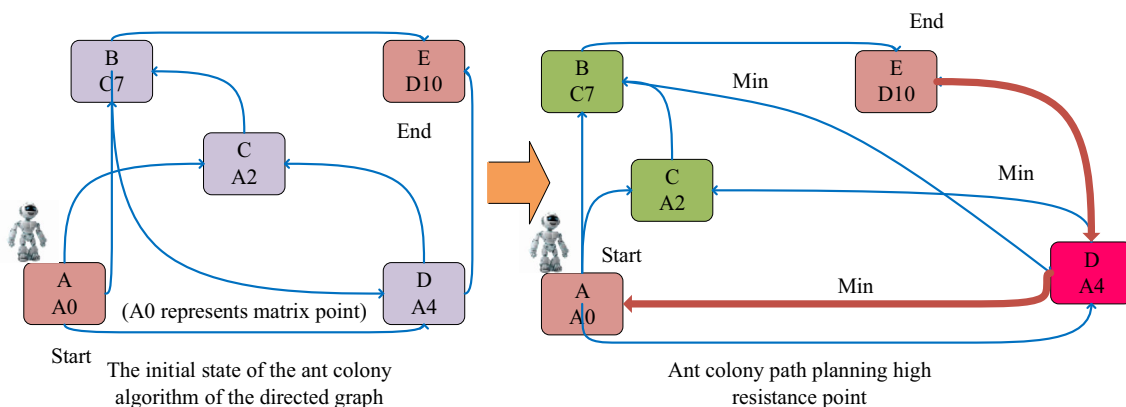


Fig. 1 Schematic diagram of robot path planning

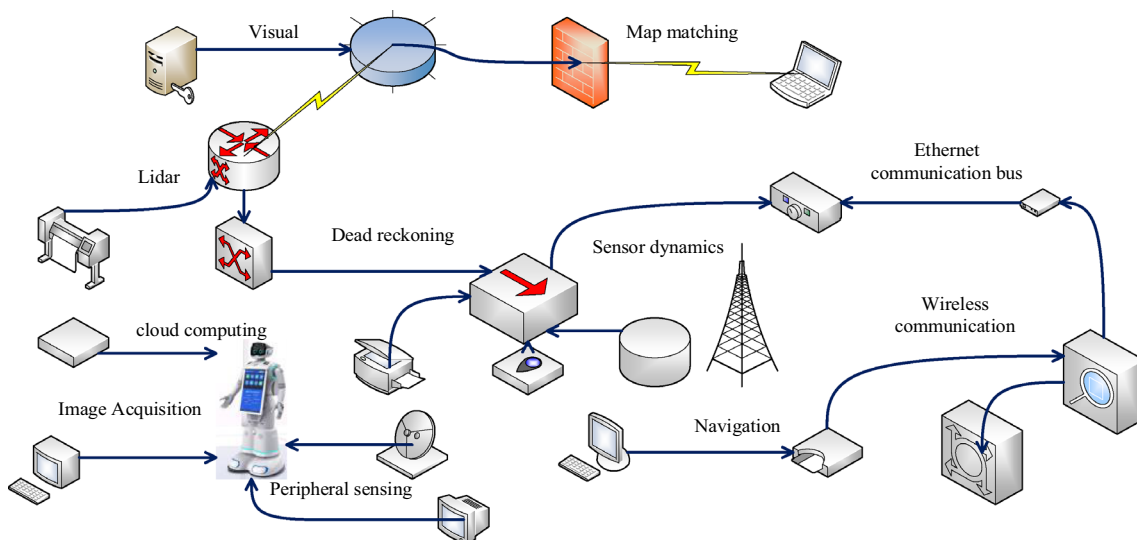
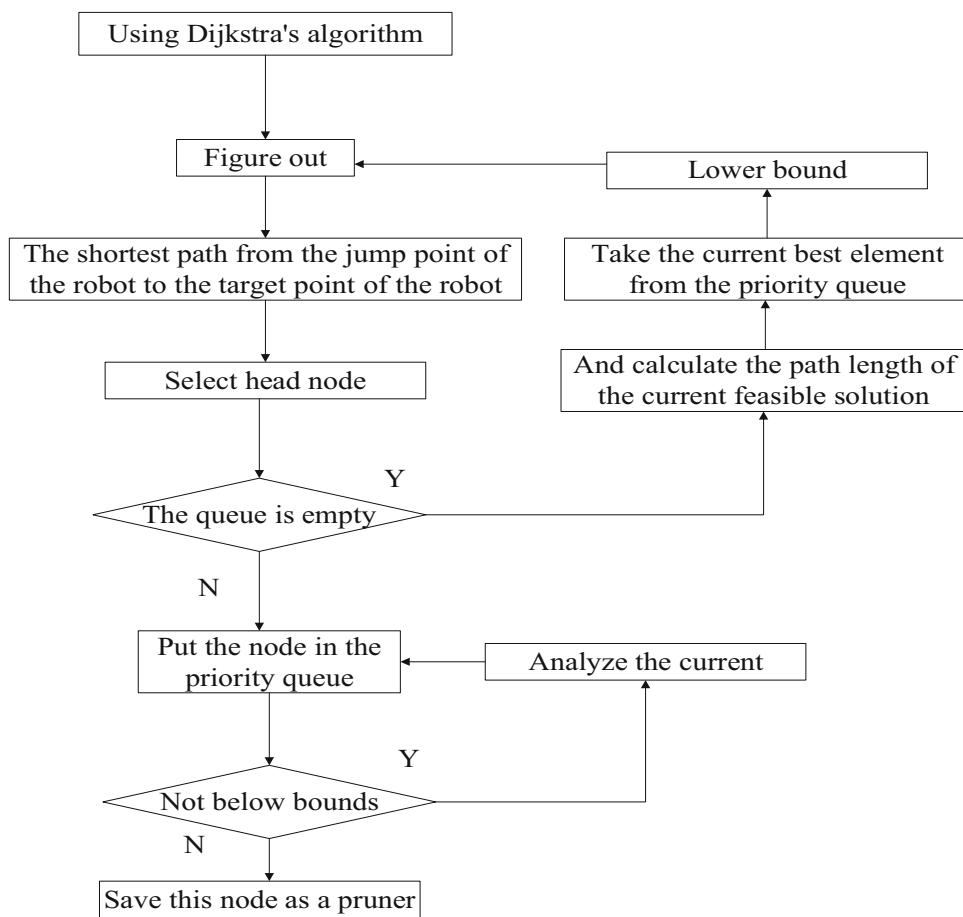


Fig. 2 Robot communication induction frame diagram

Fig. 3 Robot planning algorithm flow



$$U_{att}(x) = \frac{1}{2}k_a X - X^2 \tag{4}$$

$$U(d_i, w_j) = P(d_i)P(w_j|d_i); P(w_j|d_i) = \sum_{k=1}^K P(w_j|z_k)P(z_k|d_i) \tag{5}$$

$$P(Y) = \frac{\sigma(Y) - avg(\sigma(Y'), \sigma(Y''))}{\sigma(Y)} \tag{6}$$

where Y is the iteration number function. The repulsion field function is as follows:

$$U_{rep}(x) = \frac{1}{2}k_r \left(\frac{1}{\rho(x, x_{obs})} - \frac{1}{\rho_0} \right)^2, \rho \leq \rho_0 \tag{7}$$

$$K = \{(a_1, b_1), (a_2, b_2), \dots, (a_n, b_n)\} \tag{8}$$

$$\frac{a}{b} = \arg \max_{a_n \in W_K(a)} \sum |(b_n = c_n)M|. \tag{9}$$

Total potential field function U (x):

$$U = U_{att} + U_{rep} \tag{10}$$

$$U_{ik} = \sum_a^n \tau_1 X_{ik} + \sum_b^n \tau_2 U(Y_{ik}) + B_{ik} \tag{11}$$

$$B^{l3} = (t - y)f'(X^{l3}W^{l3}). \tag{12}$$

After the potential field function is constructed, the gravitational force, repulsion force and resultant force are obtained by gradient descent method:

$$F_{att}(x) = -grdd[U_{att}(x)] = -k_a(x - x_{goal}) \tag{13}$$

$$F(X) = F_{att}(x) + F_{rep}(x) \tag{14}$$

$$\Delta K^{l3} = -\eta\delta^{l3}X^{l3} = \eta(t - y)f'(X^{l3}W^{l3})X^{l3} \tag{15}$$

where k_a is the gravitational potential field constant, X is the robot position vector, x_{goal} is the target position vector, k_r is the repulsion potential field constant, x_{obs} is the obstacle position vector, ρ is the distance vector between the robot and the obstacle, ρ_0 is the influence distance of the repulsion field. When the distance between the robot and the obstacle is ρ_0 greater than, the repulsion field has no effect on the motion of the robot.

Besides artificial potential field algorithm, ant colony algorithm is commonly used.

When describing the mathematical model of ant colony algorithm, with the expansion of the problem scale, the traditional algorithm is almost impossible to complete, so there is still room for bionics algorithm (Pan et al. 2019; Zhao et al. 2020). Introducing random disturbances to realize the dynamic adjustment of the algorithm can avoid problems that are easy to fall into local optimization in the process of solving optimization. All NPC problems can be transformed into each other. If an algorithm can get better

performance in solving TSP, it can be considered as effective. The following is the mathematical model of TSP.

Pheromone concentration initialization:

$$T_{ij}(0) = const \tag{16}$$

$$TSP = \frac{1}{2}(t - y)^2 = \frac{1}{2}[t - f(WX)]^2 \tag{17}$$

$$\Delta X^l = -\eta \frac{\partial E}{\partial W^l} = \eta(X^l)^T \delta^l. \tag{18}$$

In the initial stage, what is the pheromone concentration between City J and City I, const is Changshu, and the value of one hundred is 0. Before the ant colony algorithm calculation, the information concentration on the path is 0.

Introducing random disturbances to realize the dynamic adjustment of the algorithm can avoid problems that are easy to fall into local optimization in the process of solving optimization. According to the value of information entropy, the next step transition probability is obtained (Chen 2021; Van et al. 2021). The calculation formula of information entropy and pheromone updating is as follows:

$$P_i = \frac{\tau_i(t)}{\sum_{ies} \tau_i(t)} \tag{19}$$

$$S = -ki \sum_{i=1}^n p_i \ln p_i \tag{20}$$

$$\tau(t) = (1 - \rho)\tau(t - 1) + \rho\Delta\tau(t). \tag{21}$$

P_i is the ratio of the amount of information on the edge I of the path to the total information, that is, $P_i > 0$. After some time, the information concentration of some path edges increases, and the entropy becomes smaller and smaller. If we do not pay attention to the adjustment, the entropy may drop to 0 (Yang et al. 2018). Then use the following function to verify:

$$\Delta w_i = -\eta E' = \eta x_i(t - y)f'(WX) = \eta x_i \delta \tag{22}$$

$$I = \frac{n \sum_{i=1}^n \sum_{j=1}^n w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^n \sum_{j=1}^n w_{ij}(x_i - \bar{x})^2} = \frac{n \sum_{i=1}^n \sum_{i \neq j} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{S^2 \sum_{i=1}^n \sum_{j=1}^n w_{ij}}. \tag{23}$$

If the moving object is regarded as a state of the studied problem, the obstacle is regarded as the constraint condition of the problem, and the collision free path is the solution to the constraint condition, then the spatial path planning is the solution of the multi constraint problem.

2.3 Real-time positioning method

At present, common space positioning technologies include infrared (optical) positioning technology, ultrasonic positioning technology, mechanical positioning technology,

positioning technology based on visual sensors, electromagnetic positioning technology, and hybrid inertial positioning technology.

In terms of robot positioning, traditional applications include dead reckoning positioning, sensor dynamic positioning, map matching positioning, visual positioning, lidar positioning. In the future development trend of positioning, more than two positioning technologies will be combined, which will not only make full use of the advantages of various positioning methods but also make up for their shortcomings. Use Hadoop cloud computing technology, wireless communication technology, Ethernet communication bus technology, navigation technology, image acquisition technology, and other technologies to solve the problem of too complex robot architecture. It can make positioning more accurate, stable, and reliable, to improve the accuracy and reliability of positioning and navigation and enhance the fault tolerance and robustness of the system. The robot path planning return function is as follows:

$$A_{\text{lim}} = f(x) = \sum_{j \in Q} c_j \frac{x_j}{\sigma(X_j')} - p - B \quad (24)$$

$$\begin{aligned} P(d_i, w_j) &= P(d_i)P(w_j|d_i); P(w_j|d_i) \\ &= \sum_{k=1}^K P(w_j|z_k)P(z_k|d_i). \end{aligned} \quad (25)$$

This will also be the main direction of future research and development. In the aspect of robot path planning, how to avoid deadlock and vibration in an unknown complex environment and how to make the robot's path globally optimal or approximately optimal are still problems to be solved. It is an obvious trend for robot path planning algorithms to be intelligent and bionic. Making full use of existing methods, researching more intelligent and information-based bionic algorithms, designing path planning and dynamic path planning methods of multi-robot systems will be the development trend in the future.

3 Path planning and real-time positioning simulation experiment design of cloud robot

3.1 Research object

Cloud computing uses Internet technology to process massive data through multiple servers at the same time. Data can be processed in parallel and distributed on different computing resources. Cloud computing has the following characteristics: flexibility, scalability, virtualization, centralization, maintenance specialization, and ubiquitous access. Transplanting the computing and processing of the robot to the cloud platform will greatly reduce the hardware development cost of the robot.

To verify the effectiveness of the method, simulation experiments are carried out on the cloud computing platform.

In the environment simulation based on the cloud computing platform, the obstacle avoidance environment is selected as the simulation object. The most common environment in the experiment is the symmetrical environment of obstacles relative to the starting and ending points. Not only because of the importance of path planning algorithms in obstacle avoidance experiments but also because in obstacle avoidance experiments, the system will place obstacles randomly. In the simulation, the experimental range is set as a square of 200×200 pixels, and the experimental boundary cannot exceed this range. The robot is a rectangle with a length and width of 4×4 pixels. Assume that the scanning range R is 35 pixels.

3.2 Experimental steps

1. Simulation of path planning in a single obstacle environment: the experiment is carried out in unit area. The starting point of the robot is $s(1.5, 1.6)$ and the target point is $g(3, 3)$. The obstacle is a rectangle.
2. Simulation of path planning in multi obstacle environment: the simulation experiment of multi obstacle planning is designed in the environment of $1010 \times$ area. The starting point of the robot is $(1.5, 1.6)$ and the target point is $g(3, 3)$.
3. Simulation of path planning in obstacle-free environment: the starting point of the robot is $(1.5, 1.6)$, and the target point is $g(3, 3)$. There are no barriers.
4. The realization of scanning simulation: the robot sensor takes the robot as the center and takes the scanning range R as the scanning skeleton to scan the area on the circle. The center of the circle is the current position of the robot, surrounded by the scanning range R . From 0° to 360° , draw a line centered on the center of the circle. The starting point and diameter of R every θ degrees, the other end of the line is the point on the circle. Set theta small enough to get the point as close as possible to the point on the circle.
5. Error handling: in the experiment, each step of the algorithm may cause error accumulation, and the cumulative error may have a great impact on the experimental results. Therefore, it is necessary to study and analyze the cumulative error and decompose the cumulative error by various methods.
6. Comparative analysis: finally, the experimental results are compared and analyzed.

3.3 Experimental data set

In the simulation experiment based on cloud computing platform, The process is programmed as a visual man–machine interface based on MFC. The waypoint of manual navigation is selected as the input data of manual navigation RRT planner through the man–machine interface. If no guidance point is selected, manual intervention of the connection planner is not required, and the manually guided RRT planner will degenerate into RRT. In different environments, 150 experiments have been carried out, and the maximum extension time is set to 30,000 times. The robot is a rectangle with a length and width of 4×4 pixels.

4 Simulation experiment analysis of intelligent robot path planning and real-time positioning algorithm under cloud computing

4.1 Path planning simulation in obstacle environment under cloud computing

As shown in Table 1, the following data are obtained after the simulation experiment on cloud computing platform, which shows the simulation results in three different environments. The starting point and target point of the mobile robot are (1.5, 1.6), (3, 3) respectively.

As shown in Fig. 4, when the mobile robot starts to get rid of the local minimum behavior, the running speed of the mobile robot is $0.2edv = MS$, and the safe distance between the robot and the obstacle boundary is $0.25safe = m$ when walking along the wall.

As shown in Table 2, it can be seen that when the actual situation of the environment matches the pre established environment, the robot can move according to the expected path of path planning.

As shown in Table 3, Comparing the positioning data with the expected data, the maximum deviation between the trajectory recorded by the robot and the expected trajectory is 13 cm, which occurs when the robot is about to reach the sub target point.

As shown in Fig. 5, the starting point and target point of the mobile robot are (3, 7), (16, 19) respectively. The starting point and target point of the mobile robot are (4, 7),

(14, 18) respectively. Assuming that the moving speed of the mobile robot towards the target is $0.5 GTV = MS$, the mobile robot can dynamically adjust its speed according to the fuzzy control rules after it starts to avoid obstacles (walk along the wall).

4.2 Compare the location data of path planning with the expected data

The schematic diagram of the path planning experiment is shown in Fig. 6, given the problem of excessive redundant points and inflection points in the path planning of the path planning algorithm, an improved path planning algorithm combining the jumping point search theory and the reverse search strategy is proposed. The algorithm eliminates unnecessary nodes and reduces computing time. And optimize the processing at the inflection point to get a smoother path. The experimental results show that, compared with the traditional robot path planning algorithm, the average calculation time is 56.09%, and the path length is reduced to 97.94%.

As shown in Table 4, compared with other global path planning algorithms, deep learning is to learn the inherent laws of path planning samples, allowing mobile robots to learn autonomously and plan feasible moving paths. It is suitable for scenarios where robots have a large number of training samples for dynamic obstacle avoidance. This is one of the key directions of path planning.

As shown in Table 5, according to the distribution of some sampling points, it can be seen that some areas are densely distributed, while others are sparse. This is mainly due to the uniform distribution of computer-generated random numbers rather than the ideal uniform distribution.

As shown in Fig. 7, the starting point and target point are not in the connection diagram, so the planning fails and the path cannot be found. This method can avoid obstacles on the planned trajectory and closely track the target; simulation results prove that the performance of this algorithm is better than the traditional APF algorithm, and it can effectively track the target.

As shown in Fig. 8, for the reason that the robot can not reach the target position: although the mobile angle planning of the robot contains the information of the target position, the modular mobile robot can only realize the path planning in the unknown environment. This paper

Table 1 Starting point and target point of mobile robot

Item	Image acquisition	Environment type	Obstacles	Vertices	Initial coordinates
Sensor dynamics	1.35	2.5	3.83	2.4	4.3
Map matching	4.24	2.19	4.26	2.71	5.12
Visual	3.93	5.04	6.4	5.41	4.59
Lidar	5.52	7.9	7.74	7.59	5.67

Fig. 4 Local minimum behavior and the running speed of the mobile robot

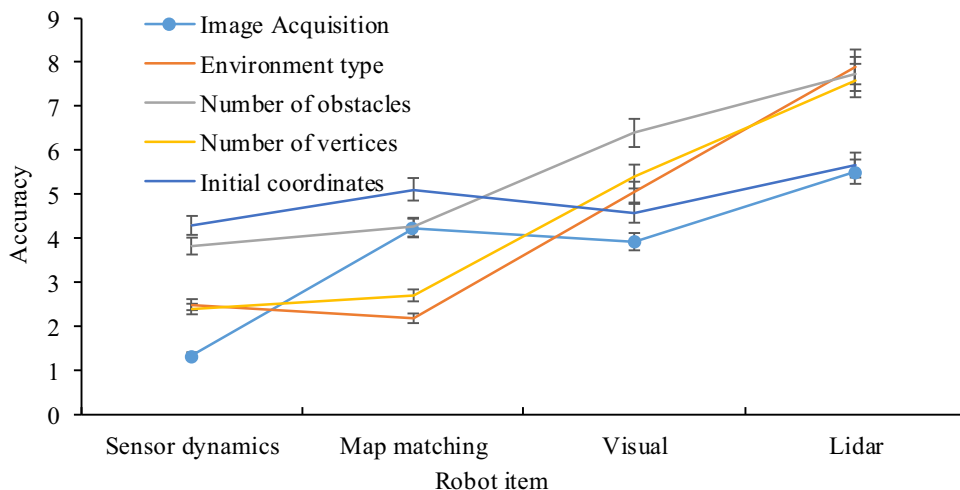


Table 2 Simulation results of path planning in obstacle environment

Environment type	Number of obstacles	Number of vertices	Algorithm time consuming	Initial coordinates	End point coordinates
Single obstacle environment	1	35	0.674	(1.5, 1.6)	(3, 3)
Multi obstacle environment	10	47	0.956	(3, 7)	(16, 19)
Barrier free environment	0	26	0.324	(4, 7)	(14, 18)

Table 3 Robot and the expected trajectory

Number	Single obstacle environment	Multi obstacle environment	Barrier free environment
200	15.4	17.58	11.74
220	16.03	18.53	10.99
240	16.31	17.2	9.25
260	14.82	16.04	8.62
280	14.38	15.53	8.58
300	15.2	16.42	7.29
320	15.95	14.63	7.83

sums up the vertical offset distances of all paths and analyzes the vertical offset degree of the paths planned by the two algorithms. The results are shown in Table 6.

To further verify the difference between the improved algorithm and the traditional algorithm in terms of path length and stability, and considering the randomness of the path search of the ant colony algorithm, 100 independent operations are performed on each algorithm, and 100 paths are planned. As shown in Table 7.

As shown in Table 8, the variable membership function is set in this policy Which is particularly important. The reason that the robot guides the target direction incorrectly may be due to a large number of input variables. To avoid

too many rules of the fuzzy controller, the fuzzy subset of the input variables is divided less. Therefore, the trend of the robot towards the target is weak, which makes it difficult for the robot to reach the target smoothly.

As shown in Fig. 9, if the robot is far away from the target, and there is no obstacle in front of the robot, and the robot runs slowly, the step size of each step of the robot is very short, and the number of steps to the end of the robot will be greatly increased.

As shown in Fig. 10, according to the robot path evaluation criteria and the experimental results of robot motion control, it is shown that this will significantly increase the time consumption and cumulative error of the robot in the

Fig. 5 Expected and actual path data

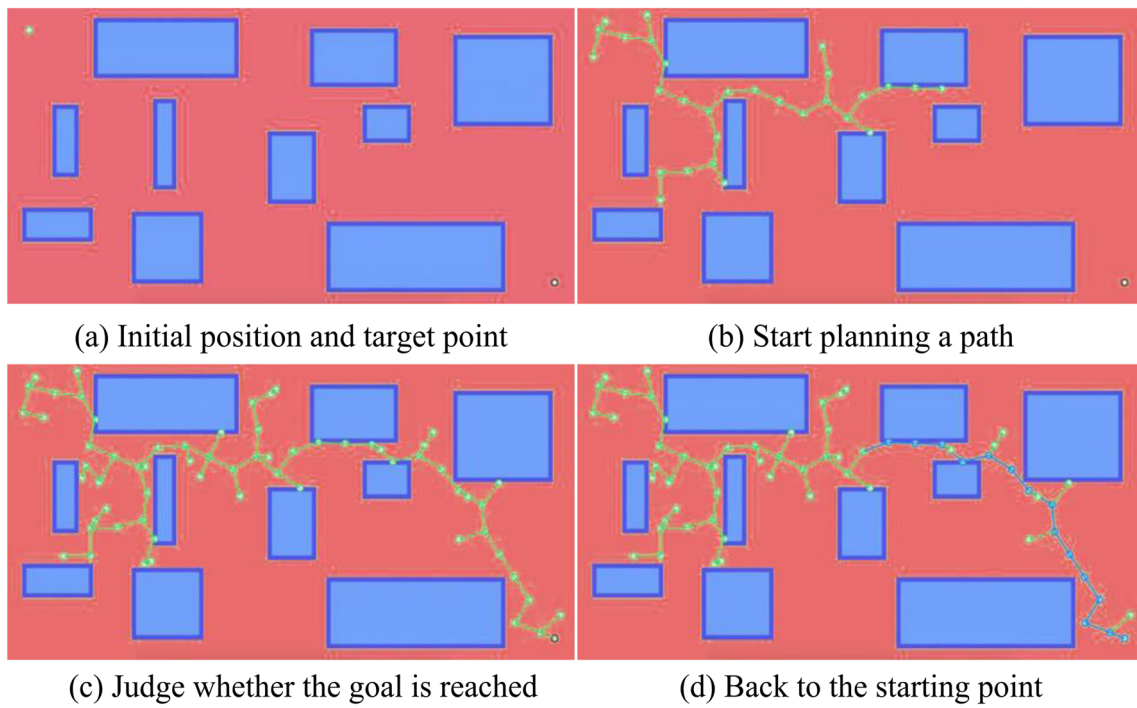
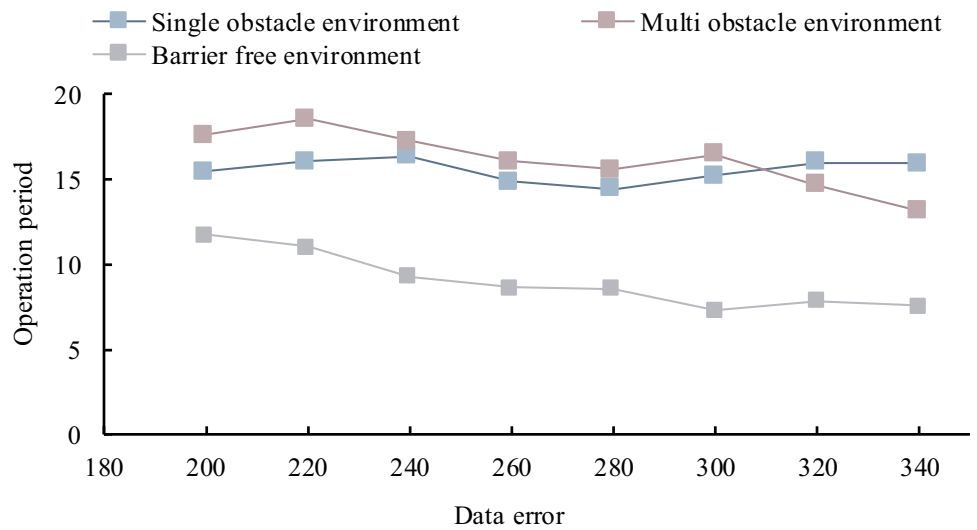


Fig. 6 Schematic diagram of path planning experiment

Table 4 Global path planning algorithms

Degree of occlusion	Environment type	Number of obstacles	Number of vertices	Algorithm time-consuming
0	9.86	15.34	10.84	15.81
20	8.63	14.05	8.9	16.52
30	7.79	13.33	6.9	14.81
40	8.6	13.06	7.18	13.97
50	9.01	11.84	7.45	14.54
60	8.72	11.05	7.22	15.08

Table 5 Distribution of some sampling points

Node Number	Single obstacle environment	Multi obstacle environment	Barrier-free environment
0	4.78	3.78	− 1.21
20	6	3.03	− 2.17
40	5.97	3.35	− 0.84
60	7.79	4.46	0.05
80	9.58	5.05	− 0.59

Fig. 7 The performance of this algorithm

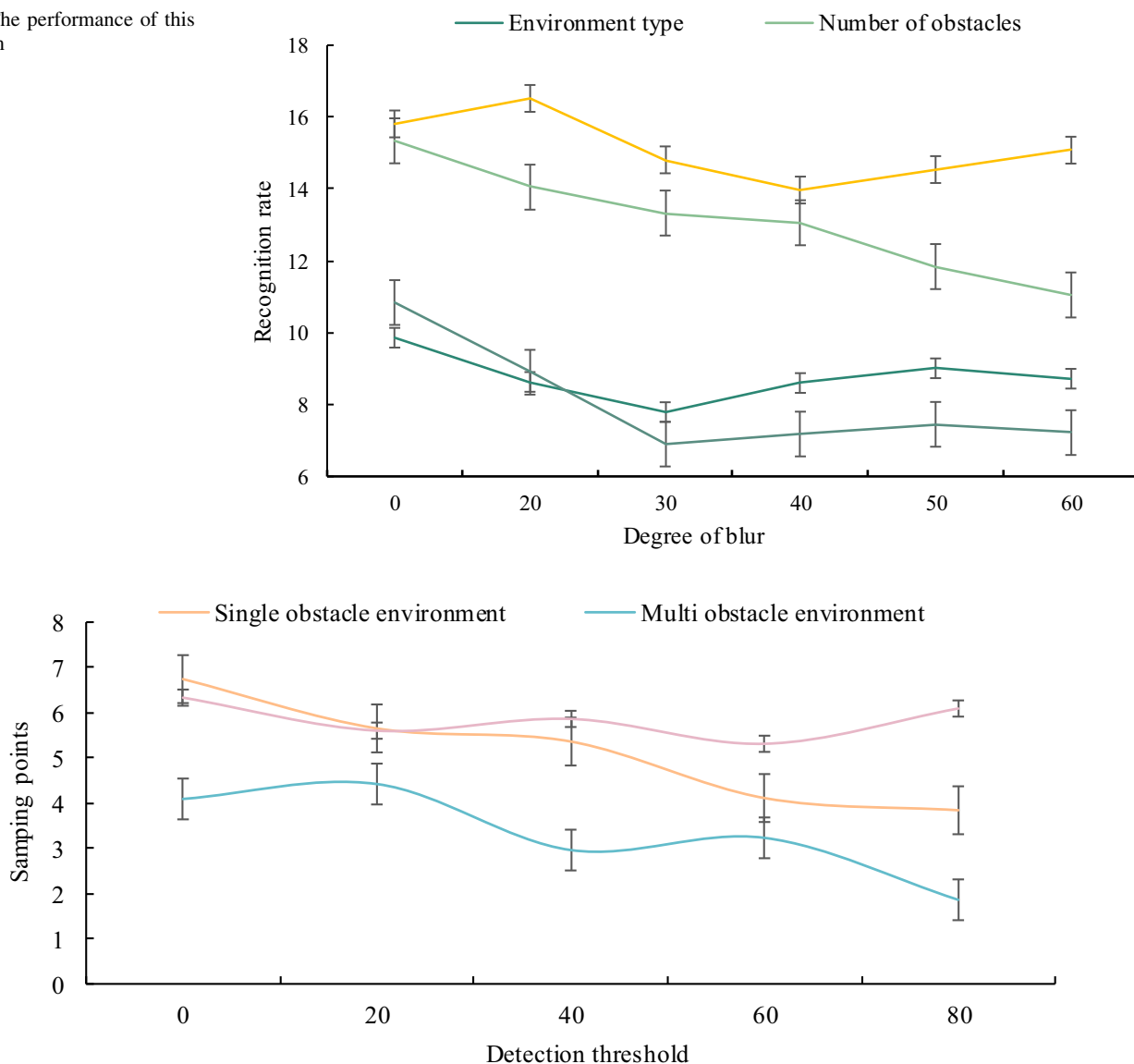


Fig. 8 Distribution of sampling points

actual operation process. If the robot is close to the target and the speed is too large, the robot cannot reach the target position due to the large step size.

5 Remote control result analysis of path planning trajectory guidance point for intelligent robot

As shown in Fig. 11, for the master–slave remote control, it takes a long time to complete the task at the beginning of the operation. The response of the robot corresponding to the command can not be well grasped. After several

Table 6 The vertical offset degree of the paths

Occlusion	Single obstacle environment	Multi obstacle environment	Barrier-free environment
0	5.96	6.89	5.57
20	6.69	6.45	6.16
30	7.05	6.79	5.19
40	5.69	5.57	5.88
50	4.68	5.28	5.65
60	3.49	5.13	3.76

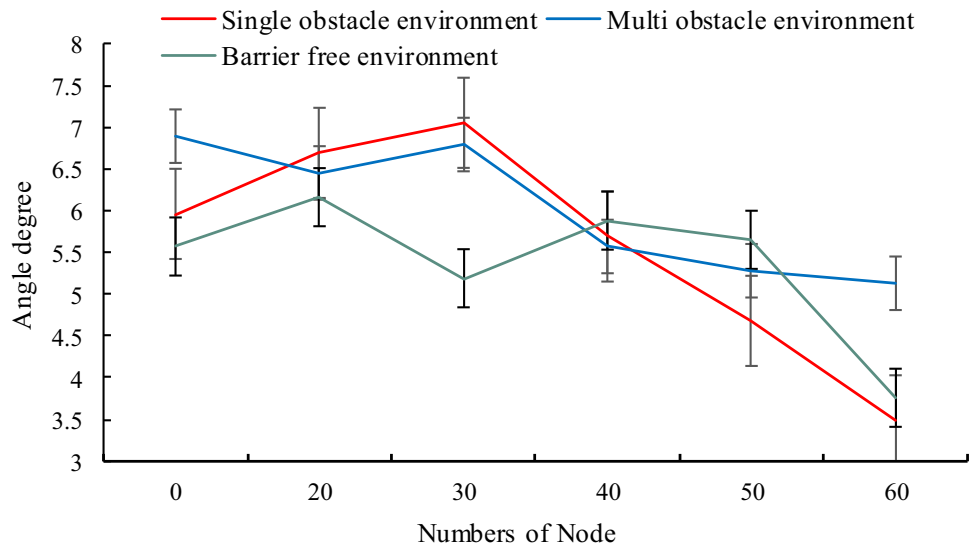
Table 7 Operations are performed on each algorithm

Item	Peripheral sensing	cloud computing	Wireless communication	Ethernet
Image Acquisition	1.06	0.65	1.15	1.3
Environment type	3.86	3.87	1.1	1.66
Obstacles	2.59	2.51	4.48	4.18
Vertices	1.2	1.08	5.51	1.11

Table 8 Target direction incorrectly

Item	Navigation	Image acquisition	Environment type	Obstacles	Vertices
Dead reckoning	4.24	2.19	4.26	2.71	5.12
Sensor dynamics	3.93	5.04	6.4	5.41	4.59
Map matching	5.52	7.9	7.74	7.59	5.67
Visual	8.15	8.78	6.9	7.21	6.47

Fig. 9 Angle and rule number of obstacles



operations, although the time consumption is reduced, the performance is unstable.

As shown in Table 9, under the same number of iterations of the improved ant colony algorithm, the path length of the best individual is always smaller than that of the traditional ant colony algorithm. The best path length for 200 iterations of the traditional ant colony algorithm is 365 m. The improved ant colony algorithm iterates the optimal path length 200 times is 337 units, which shows

that the convergence speed of the improved ant colony algorithm has been improved.

As shown in Fig. 12, this shows that the master-slave remote control relies too much on the subjective decision-making and judgment of the operator, and does not play its self-determination ability. The operator’s sense of position only comes from limited image information, so its security is high or low.

As shown in Table 10, robot path planning realizes real-time path planning based on the detected real-time

Fig. 10 Robot path evaluation criteria

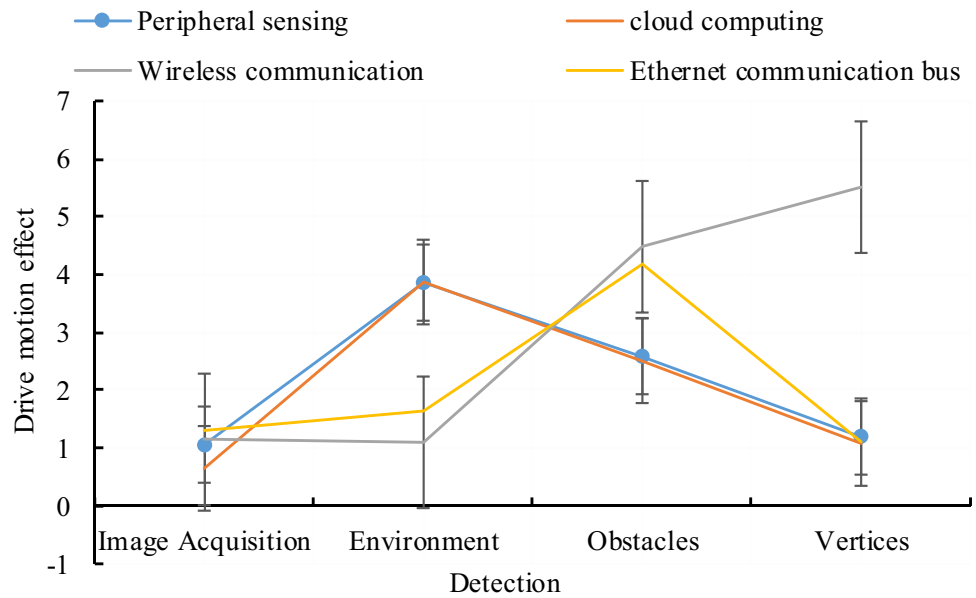


Fig. 11 Response of the robot corresponding

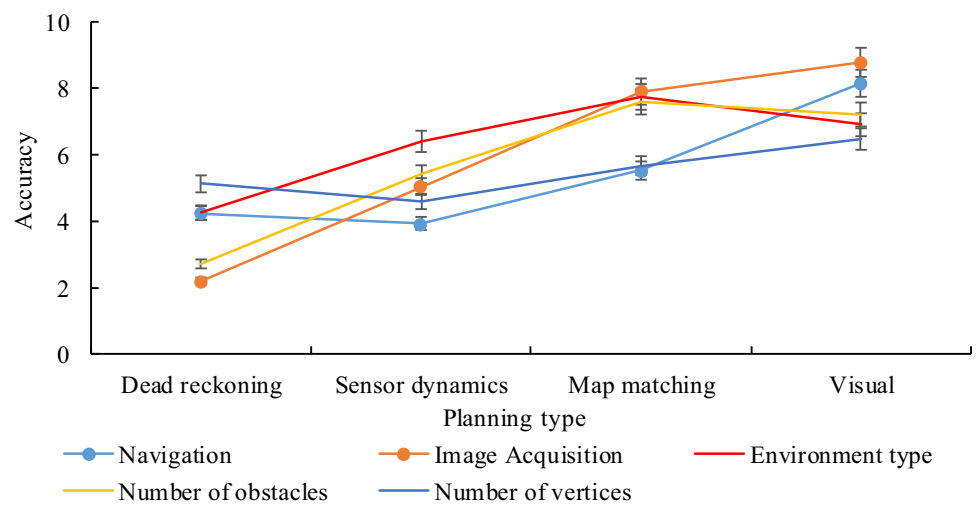


Table 9 Path length of the best individual

Item	Multi obstacle	Barrier-free	Dead reckoning	Single	Initial coordinates
Wireless	6.81	7.62	11.91	18.43	15.38
Ethernet	6.34	8.2	11.42	18.48	15.45
navigation	5.36	7.39	11.01	18.14	13.6
Image acquisition	5.75	5.84	9.07	16.88	14.38

environment information and has good obstacle avoidance capabilities. However, the algorithm cannot meet the optimal requirements of global path planning, and there is a problem of falling into local optimality.

As shown in Table 11, firstly, the improved ant colony algorithm is used for global path planning, the key points of the global path planning are selected, and the artificial potential field method is combined for local obstacle avoidance to realize the global dynamic path planning.

As shown in Table 12, the improved ant colony algorithm with a new heuristic function is introduced, which can significantly improve the path, reduce path fluctuations, jitter at individual points, and can achieve the obstacle avoidance function well; but the improved ant colony algorithm and the traditional ant colony algorithm are both cannot avoid obstacles in real-time.

As shown in Fig. 13, the experimental data of remote control of path key points show that the method takes more

Fig. 12 The operator’s sense of position

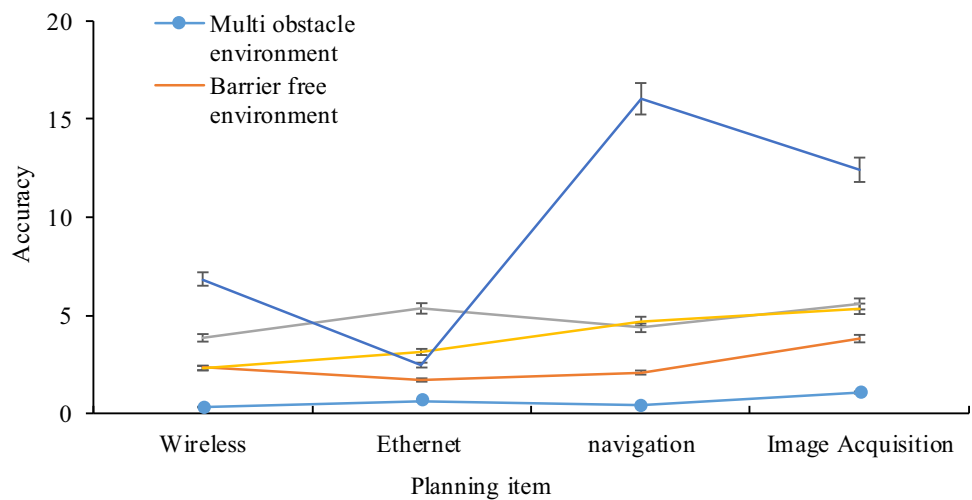


Table 10 Detected real-time environment information

Item	Single obstacle environment	Multi obstacle environment	Barrier-free environment
Image acquisition	2.15	1.64	4.55
Environment type	4	3.11	6.09
Number of obstacles	3.33	2.19	7
Number of vertices	2.9	3.91	8.3

Table 11 The artificial potential field method

Item	Multi obstacle	Barrier-free	Dead reckoning	Sensor dynamics
Environment type	1.06	0.65	1.15	1.3
Obstacles	3.86	3.87	1.1	1.66
Vertices	2.59	2.51	4.48	4.18
Time-consuming	1.2	1.08	5.51	1.11

Table 12 The improved ant colony algorithm

Item	Number of vertices	Time-consuming	Initial	Endpoint	High fidelity
reckoning	1.84	0.63	6.58	0.84	5.05
Sensor	3.01	2.05	6.21	1.86	5.25
Map matching	3.03	3.77	6.79	3.54	4.33
Visual	4.13	4.5	5.91	3.83	5.99
Lidar	5.17	3.76	5.23	5.04	7.37

time to complete the task and is relatively stable, and a considerable part of the time is spent on the selection of path key points. According to the image information, the operator selects the key points of the path at important corners so that the robot can bypass the obstacles and reach the designated area.

As shown in Fig. 14, the data of trajectory guidance points show that the time taken by the operator to complete the task is relatively stable. This is because the remote

control principle of this mode is similar to the remote control principle of path key points. The path is fitted and sent to the robot. The relatively fixed control rules of the robot determine the time-consuming stability.

As shown in Fig. 15, the difference is that the remote control terminal computer can automatically generate the control point fitting trajectory according to its attitude and the position and attitude of the trajectory guidance point, and send it to the robot automatically for execution, thus

Fig. 13 The image information and the operator selects

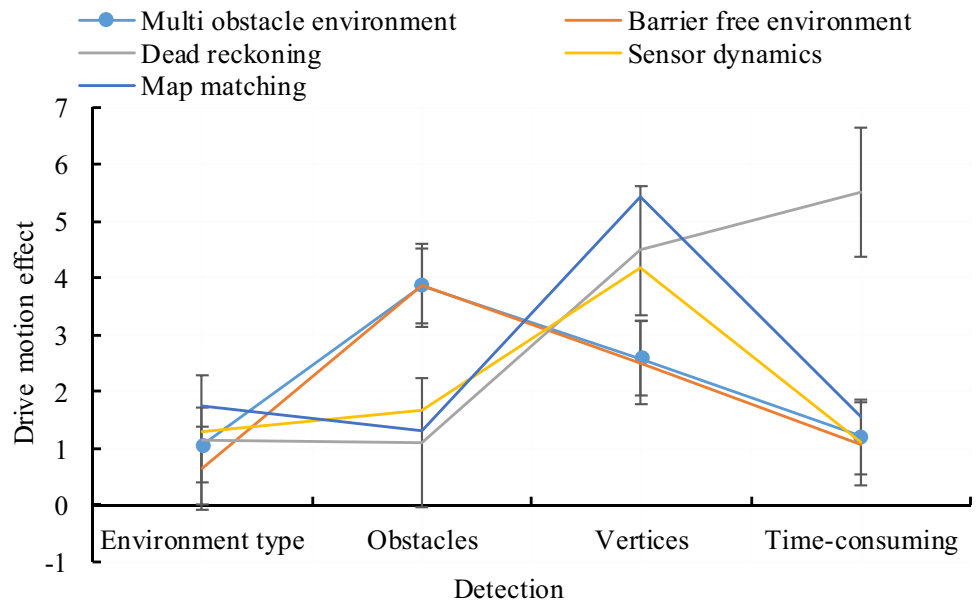


Fig. 14 Time-consuming to complete tasks in remote mode

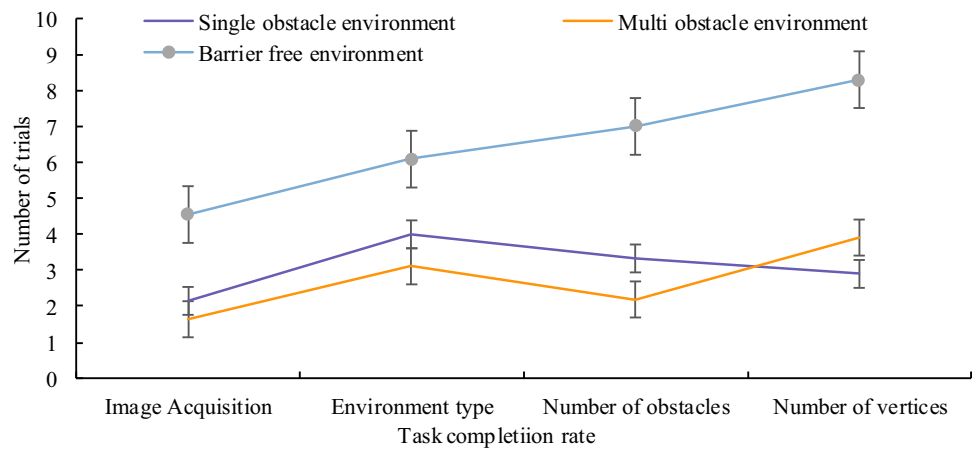
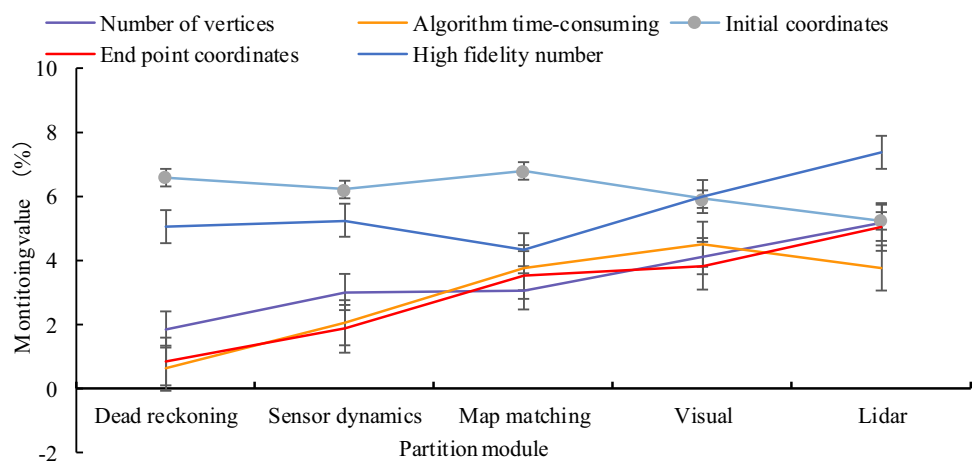


Fig. 15 The remote control terminal computer



making full use of the independence of the computer. The results show that the target can be updated online at any

time, and has good dynamic obstacle avoidance performance.

When the current fitting track is found, the image is displayed in the image. When it intersects with the dynamic or fixed obstacles on the map or the map, the operator can select the obstacle avoidance path in advance and try to stay away from the obstacles. Similarly, the disadvantage of this mode is that it requires high real-time communication, especially when the frequency of selecting guidance points is high.

6 Conclusion

Based on comparing the advantages and disadvantages of several algorithms, this paper analyzes the related deficiencies and reasons and improves the algorithms by using rough set theory. The research model of intelligent robot path planning and real-time positioning algorithm based on cloud computing is established with the improved method. The problems of robot overall path planning, local path planning, and robot real-time positioning algorithm based on cloud computing platforms are studied.

Firstly, the basic model of artificial neural networks is introduced. In this model, the mobile robot is simplified to a point, and the volume of the obstacle is expanded accordingly, and the robot moves in two-dimensional space. Firstly, a group of initial path points is obtained from the starting point and target point of the robot. Then, the position information of obstacles in the static environment of the mobile robot is described by the inequality group, and this information is taken as the input of the artificial neural network, and the collision penalty function of each path point is output through the network model. The search of the algorithm moves towards the direction that the total collision penalty function of the whole path point is reduced, and finally, the path planning of the mobile robot in the known static environment is obtained. Finally, the simulation results show that the method of an artificial neural network can accurately plan the path of a mobile robot in the known environment when the parameters are set properly. In the research process, the main innovation points are as follows: in the research of path planning and real-time positioning technology of robots based on cloud computing, a technical scheme of the path planning system for cloud intelligent robots based on distributed control is proposed. The scheme uses Hadoop cloud computing technology, wireless communication technology, Ethernet communication bus technology, navigation technology, image acquisition technology, and other technologies to solve the problem of too complex robot architecture. Three local path planning algorithms based on human–computer intelligent fusion and corresponding remote control modes are designed and improved. According to the different combinations of

human intelligence and robot autonomous performance, three semi-autonomous local path remote control methods are introduced, which are remote control of path key points and remote control of trajectory guidance points. A simple obstacle avoidance experiment was carried out. The robot path planning and real-time positioning algorithm based on cloud computing are completed to avoid obstacles and move in an unknown static obstacle environment. The overall and local path planning tasks of the robot system is completed. The introduction of a cloud computing system improves the overall planning efficiency.

In the research of this article, there are still some problems in the research of cloud computing-based path planning and real-time positioning algorithms for mobile robots, which need to be further solved. The author will continue to study in-depth.

Funding No funding were used to support this study.

Declarations

Conflict of interest These no potential competing interests in our paper. And all authors have seen the manuscript and approved to submit to your journal. We confirm that the content of the manuscript has not been published or submitted for publication elsewhere.

Ethical standards My article does not cover studies of human participants and animals.

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