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Research Progress of Robot Path Planning Algorithm

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Authors' contributions

This work was carried out in collaboration between both authors. Both authors read and approved the final manuscript.

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ABSTRACT

Path planning refers to the problem of making the robot move along a safe path and reach the end point through the corresponding planning algorithm from the starting point to the end point under the condition of multiple constraints. Firstly, the research content of path planning is briefly described. Then, the research results of path planning at home and abroad are summarized. According to the different planning methods, it is divided into traditional path planning algorithm, sampling-based path planning algorithm and intelligent algorithm-based path planning algorithm. Introduce its development status, implementation principles, applicable occasions, and existing experts and scholars ' optimization results. Finally, according to the existing path planning research results, the future improvement direction and development trend of the robot are prospected.

Keywords: Path planning; robots; planning algorithm; research result.

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1. INTRODUCTION

Path planning is one of the most important and indispensable parts of robot development and research. It is often used in the production environment to complete the task from the starting point to the end point according to certain conditions, such as speed, acceleration, angular velocity constraints and running time. In actual production and life, path planning is often used in automatic guided vehicles, automatic driving, UAV obstacle avoidance and other fields. With the increasing demand of production and people 's life, people 's requirements for planning effect are getting higher and higher, and the algorithm is constantly updated. Its optimization part often focuses on running time, number of inflection points, steering angle and so on. In today 's rapid development of the industry, due to the important position of path planning in industrial development, many experts and scholars are committed to studying new planning methods and optimizing traditional planning methods. Based on this, this paper will compare various path planning methods, analyze their advantages and disadvantages, and propose possible improvements for readers to carry out the next research. The traditional path planning algorithms mainly include A * algorithm [1], Dijkstra algorithm [2], artificial potential field method [3]. The path planning algorithms based on sampling include probabilistic roadmap algorithm [4], fast extended random number algorithm [5], intelligent bionic path planning algorithm ant colony algorithm [6], genetic algorithm [7],deep learning reinforcement algorithm and so on.

2. COMMON PATH PLANNING METHODS

According to the different search principles, the implementation process of the algorithm is also different. Commonly used path planning algorithms can be divided into traditional algorithms, sampling algorithms and intelligent bionic algorithms according to their principles.

2.1 Tradititonal Algorithm

2.1.1 Dijkstra alogrithm

Dijkstra is used to find the shortest distance from the starting point to the target point. The principle is to use the actual cost from the starting point to the surrounding point as the index, calculate the cost of the surrounding nodes respectively, take the minimum value as the new node, until it reaches the end point.

The Dijkstra algorithm calculates the cost of each point in the search range and compares them with each other to select the point with the smallest cost as the current optimal iterative solution. By continuing the process, the result of each iteration is guaranteed to be the current optimal solution. If a better solution appears in the subsequent calculation, it replaces the previous iterative solution. Therefore, when the end point is calculated, the formed path is optimal.

The priority of the Dijkstra algorithm node is determined by the size of its evaluation function value, and its evaluation function is shown in Equation

$$f(n) = g(n)\#(1) \quad (1)$$

where n is the current node, and g (n) is the sum of the cost from the starting point to the current node. The calculation method is shown in Equation

$$g(n) = \sqrt{\left(x(n) - x(s)\right)^2 + \left(y(n) - y(s)\right)^2}\#(2) \quad (2)$$

where s represents the starting point, x (n) represents the abscissa of the current node, y (n) represents the ordinate of the current node, x (s) represents the abscissa of the starting point, and y (s) represents the ordinate of the starting point.

In recent years, a large number of scholars have improved and optimized Dijkstra 's algorithm. Aiming at the problem of path conflict in Dijkstra algorithm in multipath planning of automated terminal, Huang Yihu et al.introduced the time window anti-conflict judgment model to improve it [8]. In the process of Dijkstra algorithm traversing from the source node to other nodes, the time window conflict judgment model is added to each path node. By changing the path node vector in the planning, all the previous nodes of each node are recorded in the path node vector. In all paths, a shortest path is searched to ensure that this shortest path does not conflict with other paths. Zheng et al.optimized the Dijkstra algorithm [9] for the problem that the aircraft needs to change the path when it encounters an accident in flight and requires high efficiency of path planning. The algorithm uses the normalized weight method to establish a more objective track evaluation function, which simplifies the multi-target track optimization model. The backtracking function of D algorithm is realized by pre-search to improve the relaxation of classical D algorithm and improve the planning success rate of the algorithm in complex environment. In addition, in order to improve the efficiency of the algorithm, a jump mechanism is added in the traversal process. It can meet the needs of efficient path planning in complex environments.

In order to reduce the path planning cycle, labor intensity and other freight ropeway path planning problems, Zhang Feikai et al.established an environmental model for the above problems based on Dijkstra algorithm, and proposed an adjacency matrix construction method for freight ropeway path planning based on local terrain conditions and objective functions [10].Combined with the planning method of freight ropeway, the search neighborhood of the algorithm is optimized, which effectively improves the search efficiency of the algorithm.

The above scholars have improved the Dijkstra algorithm, improved the node search method, and optimized the efficiency and reliability of the algorithm.

2.1.2 A* alogrithm

A * algorithm is a heuristic search algorithm with fast convergence speed and strong robustness [11]. It is often used in global path planning, and has the characteristics of solving the shortest path and high execution efficiency. However, in practical applications, due to the consideration of too many redundant nodes, the storage space is occupied and the search time is long. In this regard, many famous scholars have studied the optimization of A * algorithm. Common improvement methods such as changing the distance calculation method, dynamically weighting the weight of heuristic function, changing the search neighborhood, etc. But it is only suitable for static scenes. The dynamic window method is an algorithm commonly used in local path planning. It has fast response speed and moderate calculation difficulty. The next moment trajectory can be quickly obtained by speed combination. The node priority of the A * algorithm is also determined by its evaluation function, as shown in Equation (3).

$$f(n) = g(n) + h(n) \#(3)$$

Among them, g (n) is the actual cost from the starting point to the current point, h (n) is the estimated cost from the current point to the destination point, and h (n) is commonly calculated by Formula (4).

$$h(n) = \sqrt{\left(x(g) - x(n)\right)^2 + \left(y(g) - y(n)\right)^2} \#(4)$$

where x (g) represents the abscissa of the end point, and y (g) represents the ordinate of the end point. The process of the A * algorithm is shown in Fig. 1.

For the optimization and improvement of A * algorithm, different scholars have adopted corresponding improvement methods. Ren Shuyu et al.proposed a path planning algorithm combining improved A * algorithm and Lattice algorithm to solve the problems of low planning efficiency, uneven planning path and unsuitability for vehicle tracking in real environment of traditional A * algorithm commonly used in path planning of autonomous vehicles [12].This algorithm improves the search strategy and weight coefficient of the traditional A ' algorithm, improves the efficiency of global path planning, and also considers the time series, so that the obtained path has dynamic obstacle avoidance ability. At the same time, the Frenet coordinate system is used to decouple the outward and lateral motion planning in three-dimensional space, which reduces the complexity of the algorithm. Teng et al.proposed a robot path planning algorithm based on improved A * and dynamic window method to solve the problems of low search efficiency, many redundant points and poor obstacle avoidance performance of traditional A * algorithm in large-scale complex environment [13]. Aiming at the problem of low search efficiency of traditional A * algorithm, a two-way search mechanism is introduced to reduce search nodes, improve evaluation function, and improve the operation efficiency of the algorithm. Aiming at the problem of many redundant points, a method for judging the connection obstacle points is proposed, and combined with the key point selection strategy, the redundant nodes on the path can be effectively eliminated and the global path can be optimized. Finally, starting from the starting point, the key points on the optimized global path are taken as the local targets, and the dynamic window method is used for path planning in sections to ensure that the robot can avoid obstacles in real time and finally reach the target point safely. Aiming at the efficiency and accuracy of pipeline layout, Jiang Qinwen et al.proposed a pipeline initial path calculation method based on improved A * algorithm [14]. Considering the actual layout of the pipeline, the layout plan of the pipeline is obtained. The image processing module of MATLAB is used to

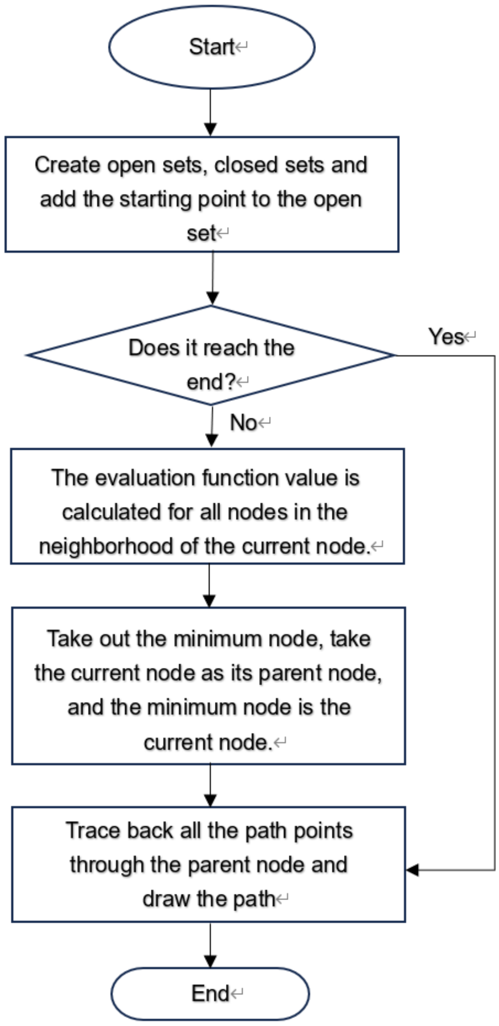

Fig. 1. A * algorithm flow chart

complete the feature extraction of the layout environment, and the grid method is used to complete the layout space preprocessing. Based on the A * algorithm, the search direction is expanded to remove redundant nodes and optimize the path length. Considering the bending constraint of the pipeline, the heuristic function of the bending number and the bending radius is constructed to screen the key nodes of the path, and an initial path of the pipeline satisfying the bending constraint and the economic constraint is calculated to reduce the workload of the path post-processing. By designing examples and analyzing the comparison results, it is proved that the algorithm proposed in this paper reduces the path length by 3.3% compared with other algorithms, improves the solution efficiency by 28.98%, and reduces the path bending nodes by 14.3%. Aiming at the problem that the traditional A * algorithm searches for more useless nodes and consumes a long time in path planning, Sun Xiaoqian et al.proposed an improved A * algorithm [15]. JPS algorithm is used to optimize the search efficiency of A * algorithm. An improved path generation strategy is proposed, and the gradient descent method is used to optimize the path length. The cubic B-spline interpolation algorithm is introduced to smooth the path. In order to verify the effectiveness of the improved A * algorithm, two kinds of obstacle areas, square and irregular, are selected and simulated on 10 groups of grid maps of different scales. The results show that the improved A * algorithm significantly reduces the traversal of invalid nodes, shortens the running time, and the searched path is smoother and shorter, which has strong search efficiency. Wei et al.proposed an improved A * algorithm based on expanding the search neighborhood to 5 × 5 random numbers to remove nodes [16] for the problem that the A * algorithm generates many inflection points and long paths. Firstly, the 3 × 3 search neighborhood is expanded to 5 × 5, so as to reduce the number of inflection points, improve the turning angle and remove redundant points. Secondly, a method of removing redundant nodes by random number is introduced. This method removes redundant nodes by randomly connecting nodes to determine whether they pass through obstacles, so as to further remove redundant nodes in the path list of A * algorithm. Finally, the improved algorithm and the A * algorithm are simulated and compared in a 30 × 30 grid map. The experimental results show that the improved algorithm has a good optimization effect in multiple sets of paths. The path length, running time and the number of access nodes are reduced by 4.46%, 24.83% and 39.93% respectively, which effectively improves the problem that the A * algorithm generates more inflection points and longer paths.

In summary, it can be seen that the optimization of A * mainly focuses on eliminating redundant nodes to improve search efficiency, reducing turning points, improving path smoothness, etc., making the A * algorithm more in line with robot kinematics in practical applications.

2.1.3 Artificial potential field algorithm

The artificial potential field refers to a method of guiding the robot to complete the movement by imitating the physical environment and applying a certain force to each object. It sets a certain gravitational force on the object that needs to be approached, and applies a certain repulsion to the object that needs to be avoided.

The artificial potential field is composed of gravitational potential field and repulsive potential field. The size of the gravitational potential field is related to the distance between the robot and the target point. The greater the distance, the greater the gravitational potential energy received by the robot. The smaller the distance, the smaller the gravitational potential energy of the robot. The size of the repulsive potential field is determined by the distance from the obstacle to the robot. When the car does not enter the influence range of the obstacle, the repulsive potential energy value is zero; after the car enters the influence range of the obstacle, the greater the distance between the two, the smaller the potential energy value of the repulsive force on the car, and the smaller the distance, the greater the potential energy value of the car.

As shown in Figs. 1-2, the robot is subjected to the repulsion from obstacles 1 and 2 and the attraction from the target point in the artificial potential field. The robot moves according to the vector sum of the forces and finally reaches the end point.

“Through the force of the artificial potential, the robot can effectively avoid obstacles to reach the target point, but there are local minima and unreachable targets in principle” [17].

In view of these two shortcomings, some scholars have made various forms of improvement and optimization. Aiming at the problem that the artificial potential field method is easy to fall into the local minimum value in the obstacle avoidance path planning of the manipulator, Zhang et al. [18] proposed an improved artificial potential field method for the obstacle avoidance path planning of the manipulator. Firstly, the envelope modeling of the manipulator connecting rod and obstacles is

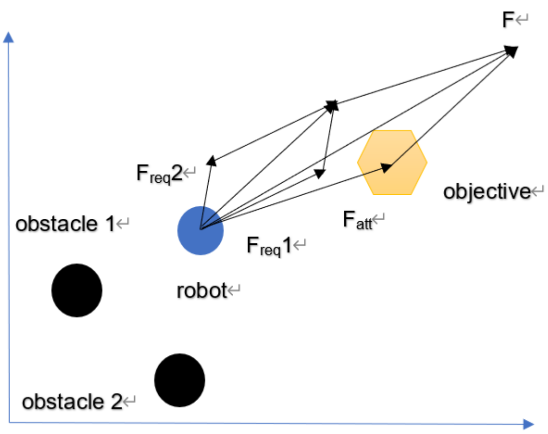

Fig. 2. Artificial potential field method diagram

carried out, and the obstacle avoidance collision detection problem is transformed into the shortest distance solution between cylinder and sphere, cylinder and cuboid. Secondly, the gravitational field and repulsive field of the target point are established in the joint space of the manipulator, and the algorithm of combining the gravitational field in the Cartesian space is established. The fast random search tree method (RRT) is used to solve the problem of the local minimum point of the traditional artificial potential field method, so that the manipulator can escape from the local minimum point and complete the obstacle avoidance path planning. Through 10 consecutive experiments, the average error of the improved artificial potential field method and the traditional artificial potential field method is calculated. The average error of the improved algorithm and the traditional algorithm is 0.01 m and 0.02 m respectively. Compared with the traditional algorithm, the target position of the obstacle avoidance planning using the improved algorithm is closer. Qiu Peng et al.designed a vehicle obstacle avoidance path planning method by improving the artificial potential field method through the established road model for the dynamic steering obstacle avoidance process of unmanned vehicles [19].Firstly, the elliptical distance is used to replace the actual distance in the repulsive potential field. Secondly, the road boundary repulsive force parameters are set to obtain the local obstacle avoidance path in the small lane space. In order to describe the driving environment and dynamic obstacle information of the unmanned vehicle more accurately, the obstacle velocity repulsive potential field is introduced. Finally, a pure tracking algorithm model with corner as the control variable is established for path tracking. Compared with the traditional artificial potential field method, the improved artificial potential field model can obtain a smooth and safe local obstacle avoidance path, and the pure tracking controller model has good path tracking performance. In order to ensure the active safety of the automatic driving vehicle in the front vehicle cut-in scene, Li Shengqin et al.proposed "an active collision avoidance path planning method based on the improved artificial potential field method" [20]. On the basis of the traditional artificial potential field method, the repulsive potential field function is changed. By increasing the repulsive potential field of the road boundary, it is ensured that the vehicle still runs in a straight line after the end of collision avoidance. At the same time, the speed adjustment factor is introduced to establish a dynamic obstacle potential field to solve the collision avoidance path planning of the artificial potential field under dynamic obstacles. The joint simulation of MATLAB and Carsim is used to simulate the proposed path planning method in the dynamic scene of the front vehicle. The results show that the improved algorithm can obtain a smooth and safe local collision avoidance path, which meets the requirements of vehicle dynamics.

In summary, the optimization of the artificial potential field method mainly focuses on improving the repulsion potential field, using the ellipse distance or the distance between the sphere and the cuboid instead of the actual distance to solve the local minimum and the target unreachable problem, and obtain a safe and smooth path.

3. SAMPLING-BASED PATH PLANNING ALGORITHM

3.1 Sampling-Based Path Planning Algorithm

Probabilistic Roadmap Method is a kind of sampling algorithm. The basic principle is to first establish the environment model, and set the corresponding obstacles, starting points and target points in the environment. Secondly, by randomly selecting a certain number of sampling points in the environment, by setting the neighborhood of the sampling point, all the sampling points in the neighborhood are connected to determine whether the connection intersects with the obstacle, thereby discarding the sampling point that collides with the obstacle. Finally, the corresponding path selection is completed through the graph search algorithm to complete the task.

This paper mainly introduces the comprehensive query method, and its process is shown in Fig. 2.

Many scholars have conducted different studies on the problem of PRM efficiency reduction when the path passes through dense obstacles or narrow channels.

Lin Junzhi et al.integrated the PRM algorithm with the artificial potential field method to solve the problem of the local minimum and the unreachable target of the traditional artificial potential field method [21]. By introducing elliptic constraints to the PRM, the sampling points that meet the requirements of the PRM algorithm are used as the local targets of the artificial potential

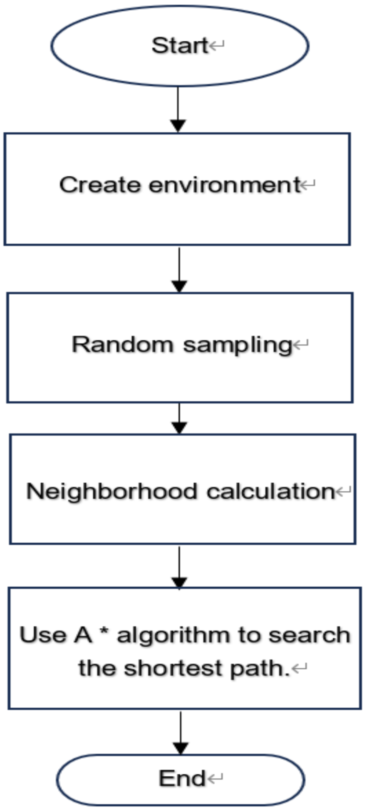

Fig. 3. PRM algorithm flow chart

field method, so as to solve the local minimum problem of the artificial potential field method. Secondly, by improving the repulsion function, the distance function between the current point and the target point is added to solve the problem of unreachable target. The results show that the fusion algorithm reduces the amount of calculation and greatly reduces the number of nodes, running time and path length. Zou et al. [22] aimed at the problem that some sampling points falling in the obstacle will be abandoned due to random sampling when the traditional PRM algorithm is sampled in the configuration space, resulting in insufficient number of sampling points. The traditional PRM algorithm is optimized, and a random node generation function is proposed to supplement the abandoned sampling points due to falling in the obstacle, and the total number of sampling points is kept unchanged. The simulation results show that the algorithm reduces the time and the number of nodes by 82.7% and 50% respectively compared with the unimproved fusion algorithm, and the path length is reduced by 28.55 m.

In terms of optimizing the PRM algorithm, it mainly focuses on integrating other algorithms and improving the sampling method of sampling points to improve the efficiency and path length of the PRM algorithm.

3.2 Rapidly Exploring Random Tree Algorithm

The RRT path planning algorithm was proposed by Lavalle in 1998. The RRT algorithm searches in space by random sampling with an initial root node, and then adds one leaf node after another to continuously expand the random tree. When the target point enters the random tree, the random tree expansion stops immediately, and a path from the starting point to the target point can be found.

The RRT algorithm has the characteristics of random sampling and probability completeness [23], so that it does not need to model the environment specifically and has strong spatial search ability. Fast path planning; it can solve the path planning problem in complex environment. The flow chart of RRT algorithm is shown in 3.

Although the RRT algorithm has the above advantages in planning the path, it also has the disadvantages of long planning time [24], many redundant points, unsmooth path and easy to fall into dead zone. In view of the above problems, many scholars have carried out corresponding research and improvement. Li Wenjie proposed an improved RRT (Rapidly-Exploring Random Tree) algorithm [25] to solve the problem that the traditional target offset RRT is easy to fall into local optimum in the environment of multi-obstacles such as yarn rack, placement platform and other cheese in the process of cheese handling. The collision detection model is established by geometric envelope method, and the distance coefficient g is added to keep the safe distance between the end of the manipulator and the obstacle. A random action selection strategy is proposed to make the tree select the expansion action before each expansion. A weakening target offset strategy is proposed to offset the extended direction according to the position of X _ goal relative to the X _ near and X _ rand connections. According to the vertical distance limit method and cubic spline interpolation, the initial path is processed to obtain a smooth path. By comparing with RRT algorithm, M-RRT algorithm, RRT algorithm with gravity coefficient and improved RRT * algorithm, the maximum decrease of path length is 23.3%, the maximum decrease of time is 82.5%, and the distance from the obstacle is always kept above 50 mm. Ma Xinguo improved the traditional RRT algorithm from three aspects [26] to solve the problems of excessive randomness in planning, low node utilization rate and non-optimal path. Firstly, aiming at the non-directional problem of RRT in the random point sampling process, the sampling rate of the target node is set, and the target point is likely to become the sampling point during each sampling, so that the path can quickly approach the target point. Secondly, the step size is dynamically set so that the robot can dynamically adjust the step size according to the number of surrounding obstacles and reduce the number of iterative steps. Finally, after obtaining a feasible path planned by the RRT algorithm, the feasible area is expanded to the surrounding area, and the feasible area is rasterized. The Dijkstra algorithm is used to find the shortest route in the feasible area and optimize the route obtained by the RRT algorithm. Finally, the obtained global path is segmented using a dynamic window algorithm. The RRT-Dijkstra fusion algorithm is compared with the RRT algorithm, the Dijkstra algorithm and the dynamic window algorithm in terms of the number of path inflection points and the path length. Experiments show that the RRT-Dijkstra fusion algorithm is more efficient and the obtained path is better. Combined with the dynamic window algorithm, dynamic obstacle avoidance can be realized.

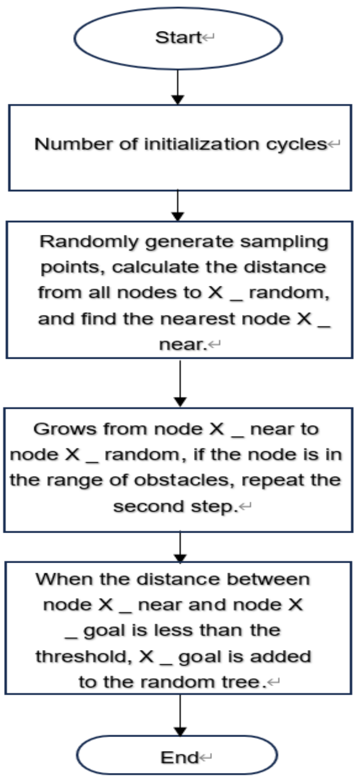

Fig. 4. RRT algorithm flow chart

In summary, the improvement of the RRT algorithm focuses on the search method, reducing the number of iterations and smoothing the path. Compared with the traditional RRT algorithm, the efficiency and path quality have been significantly improved.

4. PATH PLANNING BASED ON INTELLIGENT ALGORITHM

4.1 Ant Algorithm

Ant colony algorithm comes from the imitation of the foraging behavior of the real ant colony. The basic principle is that ants release pheromones on the distance of the path when they are foraging and the concentration of pheromones is inversely proportional to the length of the path. Later ants will choose a higher pheromone path when passing through the same place, and the pheromone concentration of the path will become larger and larger until the optimal path is found.
Compared with other algorithms, ant colony algorithm adopts positive feedback mechanism, which makes the search process converge and finally approach the optimal solution. Each individual can change the surrounding environment by releasing pheromones, and each individual can perceive the real-time changes in the surrounding environment, and individuals communicate indirectly through the environment ; the search process adopts distributed computing method, and multiple individuals perform parallel computing at the same time, which greatly improves the calculation ability and operation efficiency of the algorithm. The heuristic probability search method is not easy to fall into the local optimum, and it is easy to find the global optimal solution. However, it also has the disadvantages of blind search in the early stage [27], slow convergence speed, long time consumption, and many turns.

In view of the above shortcomings, relevant scholars and experts have conducted a lot of research on it. Zhai Zhibo et al. [28] proposed an ant colony algorithm based on Laplace distribution and dynamic window fusion to solve the problems of slow convergence, many inflection points and inability to dynamically avoid obstacles when searching paths with traditional ant colony algorithms. Firstly, the current node, the next node and the target node information are added to the heuristic information, and the dynamic adjustment factor is added to make the heuristic information strong in the early stage and the pheromone strong in the later stage of the iteration. Secondly, the Laplace distribution is introduced into the pheromone update of the ant colony algorithm to adjust the volatilization of the pheromone and accelerate the convergence speed. The path obtained by the ant colony algorithm is deleted by bidirectional redundant nodes to improve the smoothness of the path. Finally, the improved ant colony algorithm is combined with the improved dynamic window algorithm to make the robot reach the end point safely. The simulation shows that in the same map environment, the ant colony algorithm reduces the path length by 26.3% and the path inflection point by 77.7% compared with the basic ant colony algorithm.

Huo Feizhou et al.proposed an improved ant colony algorithm evacuation path planning model in a congested environment for the impact of personnel congestion on evacuation path selection during emergency evacuation [29]. Based on the two-dimensional grid environment, the trap grid is identified, the corner grid environment model is established, the initial pheromone is differentiated, and the problem of blind initial search of ant colony algorithm is improved. The heuristic function is improved by combning the influence of path congestion degree and end point on ant path selection, so as to avoid falling into local optimum and improve the quality of search path. The pheromone attenuation coefficient is introduced to punish the path through the congested area, and the sub-optimal path obtained by Dijkstra algorithm is combined to improve the update method of pheromone. Through the shortest path optimization operation, the invalid nodes and redundant turning points of the shortest path are reduced, and the path smoothness is improved.

In summary, the improvement of the ant colony algorithm mainly focuses on solving the blind search in the early stage of the algorithm, reducing the path length, and improving the smoothness, making it more suitable for path search in complex environments.

4.2 Genetic Algorithm

Genetic Algorithms (GAs) were originally developed by John Holland 's company in 1960. GAs is a nature-inspired algorithm based on the concept of Darwinian evolution, including initialization methods, evaluation of the fitness function of each chromosome, natural selection, crossover and mutation operators. GAs first randomly generate an initial population, which represents a possible solution (chromosome) to the problem to be optimized. An adaptation function is then evaluated to determine the quality of each potential solution. Then, use genetic operators to create new offspring; according to its fitness value, the parents that will reproduce are selected. By recombining the data of the parents selected in the previous step, subsequent crossovers are applied to the new offspring. Mutation is to ensure the diversity of the population by changing the genetic structure of some individuals. This evolutionary cycle is repeated until the stopping criterion is met, which can be a previously fixed algebra, or the algorithm can be stopped when the population is not involved fast enough.

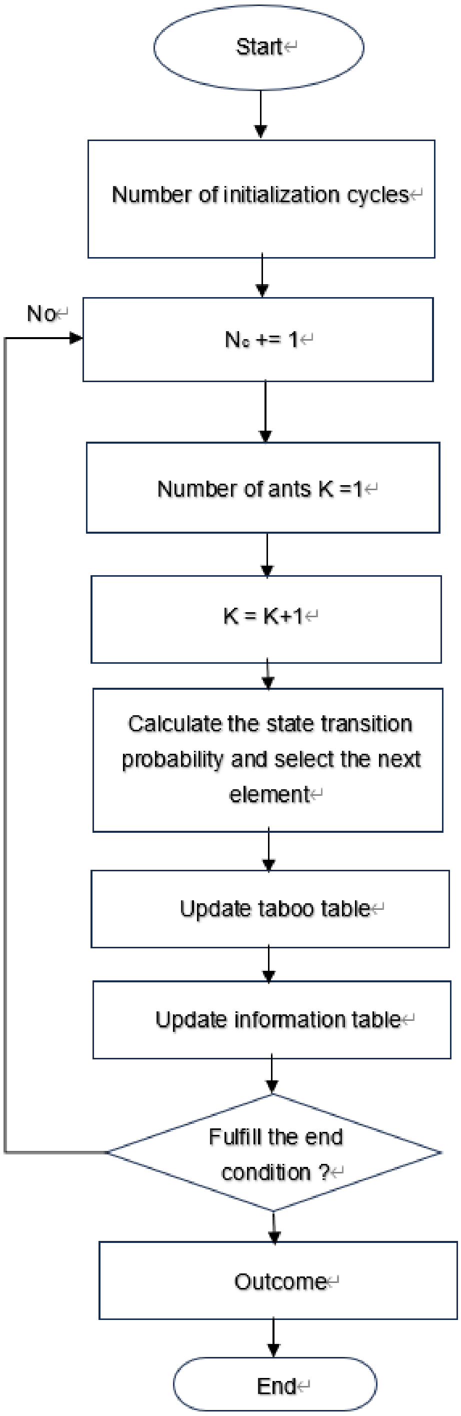

Fig. 5. Ant algorithm flow chart

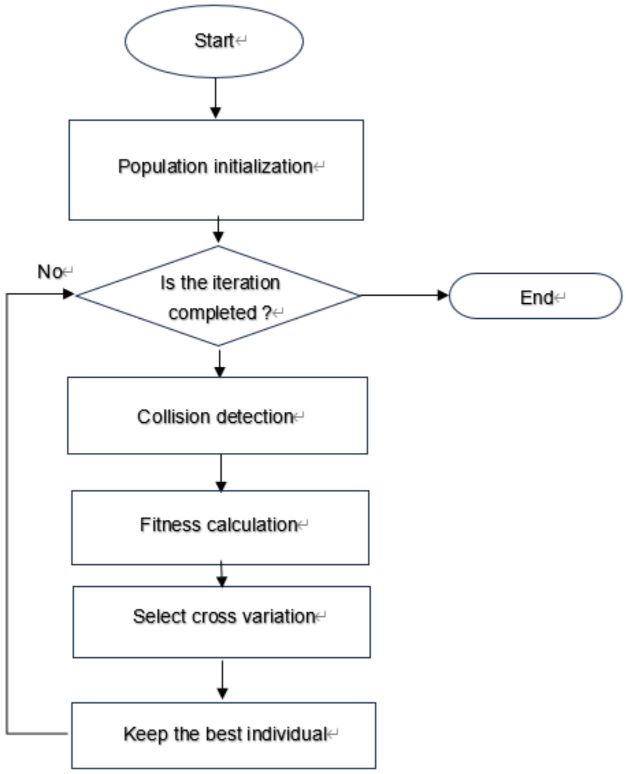

Fig. 6. Genetic algorithm flow chart

In order to improve the application of genetic algorithm, some scholars have done a lot of research. In order to solve the problems of poor path optimization ability and slow convergence speed of search algorithm under multi-constraint conditions, a robot path planning method based on improved genetic algorithm is proposed [30]. Firstly, the working environment of the robot is constructed by using the grid method, and the model is constructed with the constraint conditions of path length, smoothness and path difficulty. Secondly, the traditional genetic algorithm is improved by adding deletion operator and smoothing operator, and the niche method is introduced to avoid the algorithm falling into premature. Finally, the performance of the proposed algorithm is verified by comparative experiments. The experimental results show that the proposed method can effectively deal with the path planning problem and find the optimal path under multiple constraints. Compared with other methods, the proposed method has corresponding advantages in path length, smoothness, path difficulty and running time. Zhang Zheng et al.proposed an improved multi-objective adaptive genetic algorithm [31] to overcome the shortcomings of traditional genetic algorithm, such as slow convergence speed, premature convergence, complex and time-consuming hybrid genetic algorithm. In the initialization operation, a restricted uniform random search algorithm combined with the median insertion algorithm is proposed to initialize the population. The nodes are randomly generated by the uniform node library, and the search range of the nodes is controlled by the restrictive step size. The prior model of the restrictive step size and the length of the initial population is established. The adaptive crossover and mutation operation is improved, and its computational complexity is reduced by balancing the threshold. The adaptive evolutionary operation is used to judge the evolution, shorten the stagnation process of population evolution, and combine the greedy algorithm to prevent the population from regressing. Finally, the deletion operation is used to smooth the optimal path. Compared with the traditional genetic algorithm (GA), ant colony genetic algorithm (ACO-GA) and sparrow search algorithm (SSA), the simulation results show that the improved adaptive genetic algorithm has high efficiency, convergence with fewer times, better iterative stability, and reduces the energy consumption of the robot. Yang et al. [32] proposed an improved genetic algorithm to solve the problem that the path of the basic genetic algorithm in the path planning of mobile robots is not smooth enough and easy to fall into local optimum. Firstly, the intermediate value insertion method is used to improve the initial quality of the population. Secondly, a new fitness function is designed to smooth the path. Then the hybrid selection strategy is used to improve the premature defect of the algorithm, and the crossover operator and mutation operator are improved to increase the diversity of the population. An adaptive strategy is designed to adjust the crossover and mutation probabilities, which effectively avoids the algorithm falling into local optimum. Finally, a simplified operator is proposed to optimize the generated path twice.

In summary, the improvement of genetic algorithm mainly focuses on path length, convergence speed, running time and so on, which makes genetic algorithm more stable and more suitable for robot path planning.

4.3 Reinforcement Algorithm Based on Deep Learning

With the rapid development of artificial intelligence in recent years, it has played an increasingly important role in manufacturing, service and other industries. Deep reinforcement learning is a method in the field of artificial intelligence. It combines the perception ability of deep learning with the decision-making ability of reinforcement learning, and provides a new research optimization method in path planning.

In the aspect of deep reinforcement learning path planning, a large number of scholars focus on the shortcomings of traditional planning methods such as poor convergence and large amount of calculation, and optimize and improve the corresponding indicators to achieve better planning results. Qi et al. [33] proposed a deep reinforcement learning algorithm based on the shortcomings of traditional Q-learning algorithm, such as low efficiency and large amount of calculation. The deep neural network is used to train the robot 's execution actions and decisions to achieve the best. The convergence of Q algorithm is improved and the path is optimized. Ou et al. [34] proposed a path planning method for unmanned ships based on deep reinforcement learning to solve the problem of long delay and easy collision of traditional ship path planning. Firstly, the U-net convolutional neural network is selected to identify the electronic chart as the input, and the output is the established environment. Secondly, the path comprehensive evaluation model is established to take the minimum value of its output result as the optimal path. Finally, the simulation experiment is carried out in matlab, and the collision risk is taken as the evaluation index. The results show that the proposed method has a low collision risk.

Aiming at the problem of low efficiency of traditional obstacle avoidance planning for manipulators, Cao et al. [35] introduced a deep reinforcement learning manipulator motion planning method. By setting the corresponding parameters, the two-link manipulator and the environment model are established, and the DDPG algorithm is introduced. Through continuous execution of actions, the reward value is updated and used as experience. The neural network parameters are continuously updated according to past experience, and finally the reward value tends to converge. The results show that compared with the traditional RRT algorithm, the DDPG algorithm has a high planning success rate and a significant reduction in planning time.

In summary, the improvement of the deep reinforcement learning algorithm mainly focuses on the convergence and efficiency optimization of the algorithm, which makes the deep reinforcement learning algorithm better and can be better applied to real life.

5. CONCLUSION AND SUGGESTION

Path planning algorithm is unavoidable in robot research. Only when the planned path meets the requirements, the operation ability of the robot can be guaranteed. Although there are many kinds of path planning algorithms, it is undeniable that each algorithm has its limitations and one-sidedness, and cannot be applied to all problems. It can be improved from the following three aspects.

The defects of the algorithm structure can be improved, so that the stability and robustness of the algorithm have a certain degree of improvement.

Robot is a product of multidisciplinary integration, and various algorithms can learn from each other and integrate organically. A single algorithm has its limitations and one-sidedness, and the improved algorithm formed by the complementary advantages of various algorithms will be more universal.

The complexity of the working environment of the robot is also increasing with the wide application of the robot. In the environment with complex terrain and unclear obstacle distribution, it is required to pay more attention to real-time and obstacle avoidance efficiency in robot path planning, so as to ensure the reach of target points and the completion of established tasks. The three types of path planning algorithms discussed above have different emphases. When dealing with some complex path problems, the two types of algorithms will be used in combination to improve the success rate of path planning. According to the actual needs, the path planning algorithm will continue to optimize, which is a process of continuous improvement.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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