APPLICATION OF AN IMPROVED ANT COLONY ALGORITHM IN ROBOT PATH PLANNING AND MECHANICAL ARM MANAGEMENT

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Abstract: The purpose is to apply intelligent algorithm to the field of robot and improve the efficiency of robot path planning. First, ant colony algorithm in intelligent algorithm is expounded theoretically and computationally. On this basis, common particle swarm optimization algorithm is improved, and the improved ant colony algorithm calculation process is proposed. Finally, the simulation experiment of the robot with mechanical arm is carried out by Matrix Laboratory (MATLAB) software. The results show that the common ant colony algorithm can find the optimal path after 45 iterations, while the improved ant colony algorithm can find the optimal path after 25 iterations, which has faster convergence speed and shorter path length. There is a certain error between the actual trajectory of the mechanical arm on X-Y axis, X-Z axis, Y-Z axis and X-Y-Z axis and the ideal trajectory planned by the algorithm, and the error is about 2mm. Under random terrain conditions and U-shaped obstacle terrain conditions, the robot path planning result based on the improved ant colony algorithm is the shortest and the condition is the best; however, the robot path under the improved ant colony algorithm is reduced by about 3cm and 13cm compared with the common ant colony algorithm, and the optimal iteration times are reduced by 20 and 38 times, respectively. It shows that the improved ant colony algorithm can make the robot with mechanical arm explore the optimal and shortest path in a short time. Although there are some errors between the trajectory of the mechanical arm with the ideal trajectory, the errors are in the controllable range, that is, the improved ant colony algorithm has high efficiency.

Keywords: Improved Ant Colony Algorithm; Intelligent Algorithm; Robot; Mechanical Arm; Optimal Path.

1. Introduction

Robot technology first appeared in the 1920s, its original purpose is to replace workers to work in some simple, repetitive or high-risk, harsh environment [1]. With the development of science and technology, the robot has developed from a simple mechanical structure into a high-tech product integrating machinery, electronics, bionics, computer technology and control technology. Due to the development of robot technology, industrial robot technology and products have become an indispensable part of industrial production. It is an important tool to promote the realization of flexible manufacturing system, automatic production line and intelligent factory [2, 3].

Robot path planning is one of the core technologies in the field of intelligent robot research, and one of the key fields of robot research [4]. Path planning is to find a collision free path from the starting point to the end point in the obstacle environment according to the specific evaluation criteria. In the problem of path planning, it is necessary to consider energy consumption, the shortest time, the shortest distance and other related factors, and then formulate the optimal standard and find the starting point and target point of the optimal path according to these factors, so as to meet the demand, which is the best performance index [5]. Robot path planning problem can be a constrained path optimization problem. In order to solve the problem of path planning, a variety of tasks need to be completed, such as positioning, obstacle avoidance and so on. Some researchers put forward the research methods and development trend of robot path planning technology [6]. According to the degree of mastering environmental information, path planning of intelligent robot can be divided into global path planning based on model and local path planning based on sensor.

Global path planning refers to the path planning of robot after all working environments are mastered, which can also be called static path planning [7]. Local path planning based on sensor is to plan the path of robot when the working environment information is completely or partially unknown, which can also be called dynamic path planning [8]. With the increasing demand for robot cluster operation, traditional optimization methods are used to solve complex multi terminal operation problems, which become very difficult. Therefore, foreign scholars begin to seek inspiration from animal behavior in nature, and thus summarize swarm intelligence algorithm based on natural animal behavior to optimize the management problems encountered in multi terminal system [9].

Compared with traditional optimization methods, these methods have more practical significance and application value. Artificial neural network, artificial potential field method, genetic algorithm and other intelligent algorithms have been widely used to solve robot path planning problems [10], and attracted people's attention. Whether the environmental information is known or unknown, it has been reasonably verified and good results has been achieved. However, genetic algorithm has some shortcomings. For example, in robot path planning, it is easy to fall into the local optimal solution, the search time is long, and it is difficult to obtain the optimal results. Other algorithms also have different degrees of defects, such as slow speed, low accuracy of route planning.

Based on the common ant colony algorithm and particle swarm optimization algorithm, the two algorithms are innovatively fused, and an improved ant colony algorithm is proposed to simulate the robot with mechanical arm, so that the intelligent algorithm can be effectively applied to the robot field, and an efficient and feasible calculation method is provided for the path planning of robot and the trajectory operation of mechanical arm.

2. Method

2.1 Ant Colony Algorithm

In the process of robot path planning, the phenomena of too long planning time, low accuracy and unable to obtain the optimal solution often occur. The advantage of ant colony algorithm is that it has strong robustness in solving performance [11]. The basic ant colony algorithm model can be applied to other problems with a little modification, and it has a strong ability to search the optimal solution. It is essentially parallel and easy to implement in parallel and combine with a variety of heuristic algorithms to improve the performance of the algorithm. Therefore, the path planning of robot is based on ant colony algorithm.

After a lot of observation and research, entomologists find that ants can find the shortest path from the cave to the food source without any instructions, and can find a new shortest path with the change of environment.

This is because ants can release a kind of biological signal pheromone on their own path. They can sense and recognize the strength of pheromone, which can guide their own direction of action, and realize the communication between individuals.

Meanwhile, the number of ants on the shorter path is often more, and the pheromone content of the path is also higher than other paths, which will attract subsequent ants to choose this path. The intensity of pheromones will evaporate over time. The optimal path can be found through this positive feedback mechanism [12].

The mathematical model of ant colony algorithm is a typical traveling salesman problem (TSP), which can be described as follows. If A={A_1, A_2,…,A_m} indicates *m* nodes in map, and set H={h_{ij}|i,j=1,2,…,m; $A_i, A_j \in A$} denotes a straight path and connects the *n* nodes on it, the length of the path is represented by the set l_{ij}(I,j=1,2…,m). The essence of TSP is to find a route with the shortest total distance in the closed loop and pass through all the nodes in the graph, as shown in Figure 1 below:

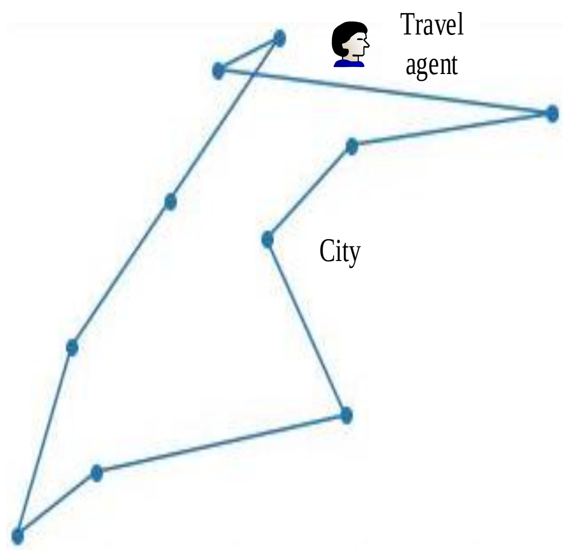

Figure 1: Diagram of TSP problem

If the number of ant colony in ant colony is *n*, and the size of pheromone on path h_{ij} in time t is $\varphi_{ij}(t)$, the size of pheromone of all paths in planning space can be expressed by set Q, namely Q={$\varphi_{ij}(t)$|i,j=1,2,…,m; $A_i, A_j \in A$}. When t = 0, there will be a certain number of pheromones in each path, and the value of $\varphi_{ij}(0)$ is equal. The process of exploring the optimal path of the algorithm is to optimize the algorithm by changing transition probability, local pheromone and global pheromone update rules in the directed graph P = (A, H, φ). It includes three parts: transition probability rule, local optimization rule and global optimization rule.

The rule of transition probability is to record the nodes that the ants x (x = 1,2, ..., n) pass by in taboo list [13]. In the optimization process, the search direction of ant *x* is determined by the size of pheromone on the path. At time *t*, the probability of ant *x* transferring from current node *i* to next node *j* is expressed by P_{ij} (t).

The equation is as follows.

$$P_{ij}^{x}(t)=\begin{cases}\dfrac{\varphi_{ij}^{\lambda}(t)\gamma_{ij}^{\mu}(t)}{\sum\varphi_{ij}^{\lambda}(t)\gamma_{ij}^{\mu}(t)} & j\in allow_{x}\\ 0 & \text{others}\end{cases} \tag{1}$$

In (1), λ represents pheromone heuristic factor, which represents the degree of interaction between each ant; μ represents expected value heuristic factor, which represents the degree of influence of surrounding environment on ants; $allow_x$ represents the set of nodes to be selected, and $\gamma_{ij}^{\mu}(t)$ represents heuristic function, which is the reciprocal of distance between nodes. The equation is as follows.

$$\gamma_{ij}^{\mu}(t)=\frac{1}{h_{ij}} \tag{2}$$

Local optimization rule means that every time the ant completes the path search, it needs to update the pheromone on the path. If the starting time is t and the search time is $\triangle$t, the local pheromone optimization rules are as follows:

$$\varphi_{ij}(t+\triangle t)=(1-\delta_1)\varphi_{ij}(t)+\delta_1\varphi_0 \tag{3}$$

$$\varphi_0=U_1/mh_{\min} \tag{4}$$

$\delta_2\subset[0,1]$ represents the attenuation coefficient of the local pheromone. h_{min} represents the shortest distance between two nodes, and U_1 represents the intensity of local pheromone.

Global optimization rule means that when all ants in the iteration complete the search from the start to the end, they need to change the global pheromone.

The changing rules are:

$$\varphi_{ij}(N+1)=(1-\delta_2)\varphi_{ij}(N)+\delta_2\triangle\varphi_{ij}(N) \tag{5}$$

$$\triangle\varphi_{ij}(N)=U_2/\min\sum_{i=1}^{m-1}h_{i,j+1} \tag{6}$$

$\delta_2\subset[0,1]$ indicates the attenuation coefficient of the global pheromone, N represents the number of iterations of the algorithm currently used, $\triangle\varphi_{ij}(N)$ is the number of pheromone changes in this iteration, $\min\sum_{i=1}^{m-1}h_{i,j+1}$ represents the mileage of the optimal path in this iteration, and U_2 indicates the intensity of the global pheromone.

2.2 Improvement of Ant Colony Algorithm

Although ant colony algorithm has strong robustness, parallelism, self-organization, positive feedback and other advantages, its disadvantages are also obvious. For example, when it is used to deal with large-scale combinatorial optimization problems, there will be some shortcomings, such as slow convergence speed, easy to fall into local optimum, poor optimization results, and incomplete search [14]. In addition, in view of the particularity of the mechanical arm, it is necessary to find the optimal solution in the shortest possible time, which requires high real-time performance, so it is necessary to optimize the algorithm.

First, the improvement based on particle swarm optimization algorithm [15]. Particle swarm optimization is a population optimization algorithm designed by Kennedy and Eberhart based on the study of birds' foraging behavior in nature. In this algorithm, each particle represents a potential solution of the optimization problem, and its value is measured by the fitness value of the particle. In order to judge the fitness value, it is necessary to design a reasonable evaluation function, and then judge according to the speed and position information of particles. In each iteration of the algorithm, the position and speed of the individual are updated by comparing the optimal solution of the particle with the optimal solution of the whole population.

The number of particles is set to M and the search space is set to N dimensions. The position of the k-th particle is expressed as X_k=X_{K1}, X_{K2},..., X_{KN}) and the velocity is expressed as V_k=(V_{k1}, V_{k2},...V_{kN}). The best position of the k-th particle is L_{best}, and all particles are represented as T_k=(T_{k1}, T_{k2},..., T_{kN}). The best individual in the set is R_{best}. Then, in the process of searching, the speed and position of particle k are updated in the way as follows:

$$V_{kc}^{j+1}=E*V_{kc}^{j}+S_1f_1\left(T_{kc}^{j}-X_{kc}^{j}\right)+S_2f_2\left(T_{kc}^{j}-X_{kc}^{j}\right) \tag{7}$$

$$X_{kc}^{j+1}=X_{kc}^{j}+V_{kc}^{j} \qquad 1\le k\le M, 1\le c\le N \tag{8}$$

E is the inertia factor, j is the number of iterations, and V_{kc} is the flight speed of particles in the c dimension. S_1 and S_2 represent acceleration factors, which are normally normal. f_1 and f_2 are random values in the range of [0,1]. In order to accelerate the iterative speed of the algorithm, it is necessary to reduce the probability of blind particle search. Generally, [$X_{c,min}$, $X_{c,max}$] and [$V_{c,min}$, $V_{c,max}$] are used to limit the active area and speed range of particles.

Then, the optimization of the algorithm. The core idea of the fusion of particle swarm optimization and ant colony algorithm is to use particle swarm optimization algorithm to optimize the important parameters of ant colony algorithm. The traditional empirical mode selection is changed through the adaptive selection of particle swarm search, in order to improve the accuracy of the algorithm. The specific method is to take the parameters of ant colony algorithm as the position information of particle swarm algorithm, use the position information of particle swarm to run ant colony algorithm, design an appropriate evaluation function to evaluate the results, and further guide the direction of convergence of particle swarm algorithm to improve ant colony algorithm. The steps of the hybrid algorithm are as follows

In the first step, the particle swarm optimization algorithm is initialized, the initial position and velocity of each particle are randomly selected, and the values of acceleration factor and inertia factor are given.

In the second step, the position information of particles is regarded as an important parameter of ant colony algorithm. By running ant colony algorithm, the path length, stability, convergence speed, running time and other data corresponding to the particle position information are obtained; the above data are introduced into the evaluation function of particle swarm algorithm to evaluate the results, and the fitness value of each particle is obtained.

In the third step, the fitness value of each particle's current position is compared with that of L_{best}. If the result is better, it is necessary to update with the current location. Otherwise, the current position is not changed. The fitness value corresponding to the L_{best} of each particle is compared with the global extreme value R_{best}. If the result is better, the current location is used for L_{best} update.

In the fourth step, according to equations (7) and (8), the position and speed of each particle in the particle swarm optimization algorithm are updated, and whether the number of iterations meets the maximum is judged. If it is satisfied, the output is globally optimal. Otherwise, it is necessary to go back to step 2; the position information corresponding to the global optimal R_{best} is taken as an important parameter of the ant colony algorithm. The ant colony algorithm is run for path planning, and the solution obtained is the optimal path.

The pheromone upper and lower limit setting is very important, because in the optimization process of ant colony algorithm, the size of residual pheromone on the path seriously affects the judgment of ants and determines the quality of convergence results. When pheromone concentration is too high, ant search will lose its randomness and the algorithm will fall into local optimization. On the contrary, when the pheromone concentration is too low, the algorithm is easy to fall into premature convergence [16,17]. Therefore, by setting the upper and lower limits of pheromone concentration, the size of residual pheromone on each path is limited in the interval [η_{min}, η_{max}]. It avoids the premature and local optimum of the algorithm, and enhances the positive feedback effect of the algorithm

$$\eta_{kc}(t)=\begin{cases}\eta_{max} & \eta_{kc}(t)\geq\eta_{max}\\ \eta_{o} & \eta_{min}<\eta_{kc}(t)<\eta_{max}\\ \eta_{min} & \eta_{kc}(t)\leq\eta_{min}\end{cases} \tag{9}$$

η_o represents the size of pheromone obtained by global update calculation.

Finally, the path planning steps of the mechanical arm based on the improved ant colony algorithm are as follows

First, the construction of environment model. The working environment and obstacle information of the mechanical arm are determined, the initial point and target point of the path to be planned are given, and the environment model is established by using grid method [18], which provides conditions for ant colony algorithm.

Second, three-dimensional path planning. Ant colony algorithm is run to search in the given space and get the optimal path that meets the requirements. In order to avoid the vibration of the mechanical arm, the quadratic B-spline curve method is used to smooth the inflection points of the path planned by ant colony algorithm. The optimized path is the motion path of the mechanical arm end effector.

Third, the inverse kinematics solution of the mechanical arm [19]. Through ant colony algorithm, the position information of nodes on the path is obtained, and the corresponding joint angle of each node on the path is obtained. If the inverse solution fails, it means that the path node is beyond the working range of the mechanical arm, and it is necessary to return to step 2 for path planning again.

Fourth, the forward kinematics of the mechanical arm [20]. Because of the non-uniqueness of the inverse solution, the combination of eight joint angles can be obtained after the inverse solution of each path node on the planning path is solved. According to the principle of minimum angle, the optimal solution is selected to solve forward kinematics, and the spatial coordinates of each joint of the mechanical arm are obtained.

Fifth, collision detection. After the spatial position of each joint is obtained through forward kinematics, according to the collision detection method in section 3, the line equation between two adjacent joints is calculated to further judge the position relationship between the mechanical arm and the obstacle. If there is a collision, it is necessary to go back to step 4 and select other solutions of 8 joint angle combinations. If all the solutions do not meet the obstacle avoidance requirements, the path node should be recorded as the obstacle avoidance point, and the corresponding position of the obstacle matrix should be changed to 1. Moreover, it is necessary to return to step 2 and re plan the path until the collision requirements are met.

Figure 2 is the flow chart of path planning of the mechanical arm under the condition of improved ant colony algorithm.

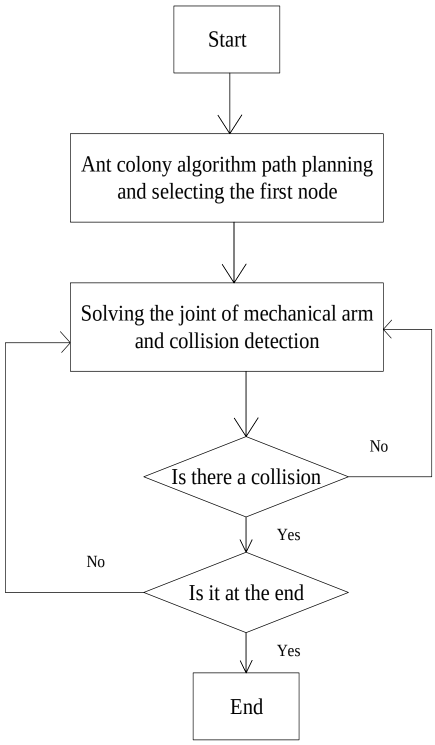

Figure 2: The flow chart of path planning of the mechanical arm under the condition of improved ant colony algorithm

2.3 Parameter Setting and Analysis Tools

First, the workspace of the mechanical arm is assumed to be a 2*2*1m cube with three same identical obstacles. The size simplified with the cuboid envelope method is 0.5*0.5*0.5m, and the coordinates of initial point and target point are (7, 17, 2) and (12, 8, 4), respectively. The grid method is used for environment modeling, and the size of grid block is set to 0.2*0.2*0.2m.

Then, table 1 is the parameter setting of the improved ant colony algorithm.

Table 1 Parameter setting of improved ant colony algorithm

Parameter	Value
η_0	2
η_{min}	0.5
η_{max}	5
δ_1	0.3
δ_2	0.5

Finally, environment modeling, algorithm programming and simulation analysis are carried out by using Matrix Laboratory (MATLAB) software. The RobotStudio software is used to record the actual trajectory of the end effector of the manipulator. Origin 2018 64Bit is used to analyze the data visually.

3. Results and Discussion

3.1 Comparison of Convergence Curves between Improved ant Colony Algorithm and Common ant Colony Algorithm

The convergence curves of path length and average path length changing with the number of iterations are compared between the improved ant colony algorithm and the common ant colony algorithm. Figure 3 presents the result.

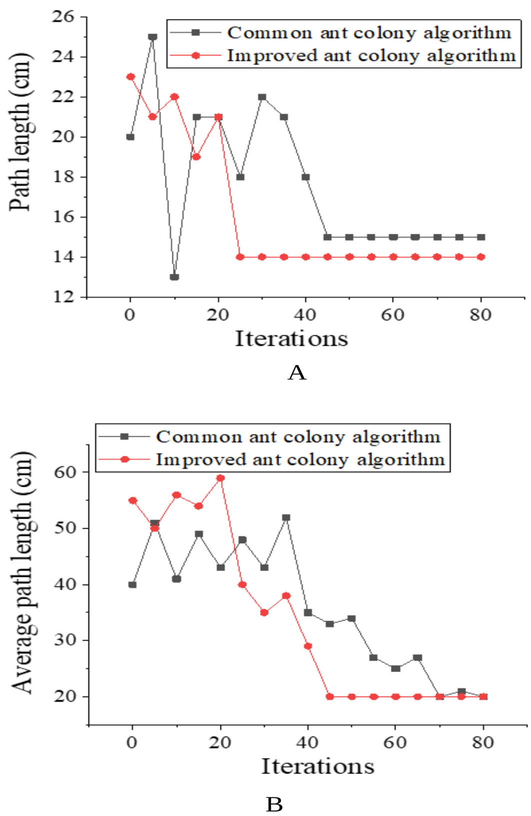

Figure 3: Comparison of convergence curve between improved ant colony algorithm and common ant colony algorithm (A: the change of path length with the number of iterations; B: the change of average path length with the number of iterations)

Figure 3A suggests that the common ant colony algorithm only explores the optimal path after 45 iterations, and its convergence speed is relatively slow; the improved ant colony algorithm explores the optimal path after 25 iterations, its convergence speed is relatively fast, and the planned path length is relatively short. Figure 3B reveals that the average path length of the common ant colony algorithm does not reach the optimal value, while the average path length of the improved ant colony algorithm reaches the optimal value after 45 iterations.

3.2 Path Planning Results of Robot Mechanical Arm

The actual trajectory data of the mechanical arm is visually analyzed, and Figure 4 presents the results.

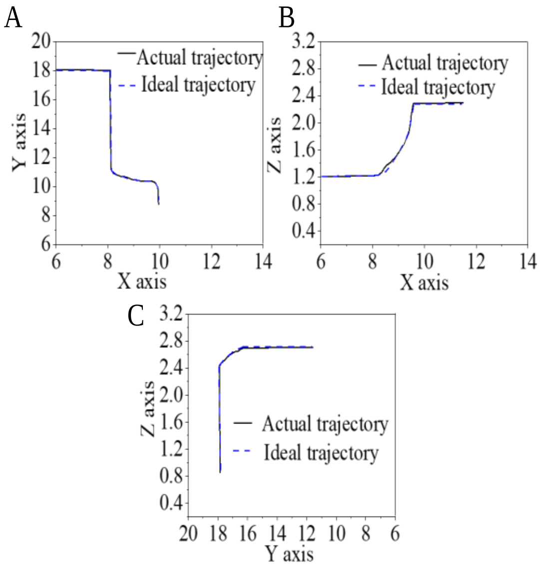

Figure 4: Trajectory of mechanical arm in different two-dimensional planes

Figure 4 shows that there is a certain error between the actual trajectory of the mechanical arm on X-Y axis, X-Z axis and Y-Z axis and the ideal trajectory planned by the algorithm, and the error is about 2 mm.

Figure 5 shows the three-dimensional trajectory of the mechanical arm.

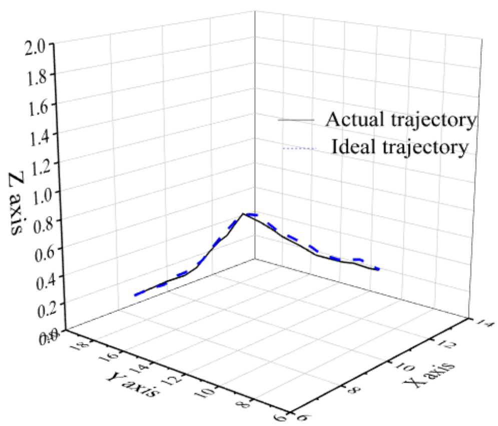

Figure 5: Trajectory of mechanical arm in three-dimensional space

Figure 5 shows that there is a certain error between the actual trajectory and the ideal trajectory planning, which is about 2mm. There are two main reasons. One is to keep only four decimal places in the calculation of mechanical arm inverse kinematics, which will undoubtedly lead to the accumulation of errors.

The other is that the path planning algorithm depends on the ideal mechanical arm kinematics model, which inevitably exists in the use of mechanical arm. All these factors will lead to wrong actual motion model and theoretical motion model, which will lead to error motion trajectory.

3.3 Path Planning Results of Robot Under Different Obstacles

Random terrain and U-shaped obstacle terrain are designed. Figure 6 shows the path planning result of the robot.

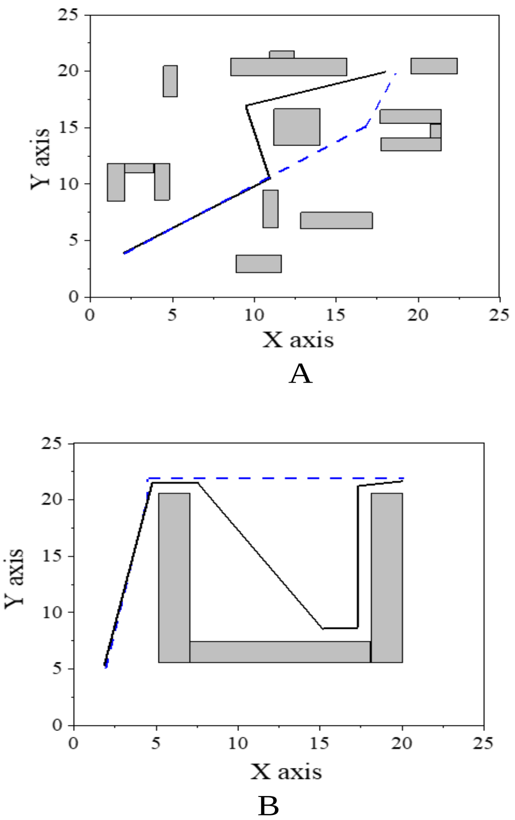

Figure 6: Path planning of robot in random terrain and U-shaped obstacle terrain (A: random terrain, B: U-shaped obstacle terrain (solid line represents common ant colony algorithm, and dotted line represents improved ant colony algorithm))

Figure 6 suggests that under random terrain conditions, the shortest distance of robot path planning based on common ant colony algorithm is 21.165cm, and that based on improved ant colony algorithm is 18.121cm, which indicates that the improved ant colony algorithm can make the shortest path planning result of robot. Under the condition of U-shaped obstacle terrain, the shortest distance of robot path planning based on common ant colony algorithm is 27.322cm, and that based on improved ant colony algorithm is 19.481cm, which also shows that the improved ant colony algorithm can make the shortest path planning result of robot.

3.4 Comparison of Different Algorithm Parameters in Different Terrain Environment

The parameters of the common ant colony algorithm and the improved ant colony algorithm in random terrain are analyzed visually. Figure 7 presents the results.

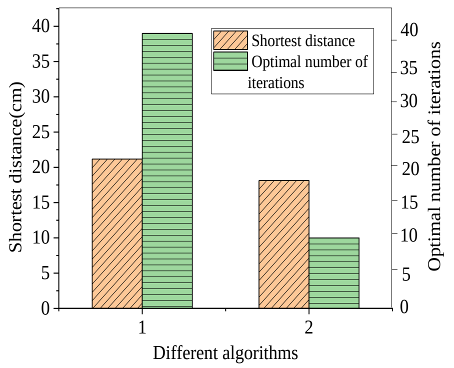

Figure 7: Comparison of parameters between common ant colony algorithm and improved ant colony algorithm under random terrain (1: common ant colony algorithm 2: improved ant colony algorithm)

Figure 7 reveals that in the random terrain environment, the robot path planning under the improved ant colony algorithm is the shortest, which is about 3cm less than the common ant colony algorithm, and the optimal number of iterations is reduced by 20 times.

Then, in the U-shaped obstacle environment, the parameter results of the common ant colony algorithm and the improved ant colony algorithm are analyzed visually. Figure 8 presents the results.

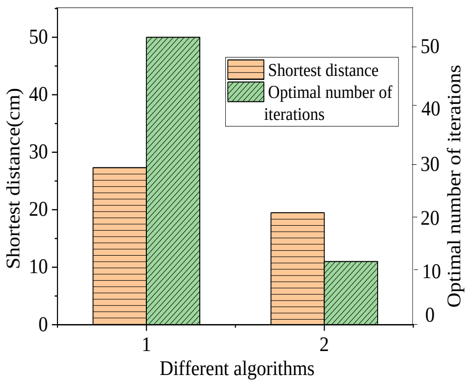

Figure 8: Comparison of parameters between common ant colony algorithm and improved ant colony algorithm under U-shaped obstacle terrain (1: common ant colony algorithm 2: improved ant colony algorithm)

Figure 8 indicates that in the U-shaped obstacle terrain environment, the robot path planning under the improved ant colony algorithm is the shortest, which is about 13cm less than the common ant colony algorithm, and the optimal iteration times are reduced by 38 times.

4. Conclusion

Based on the theory and calculation basis of ant colony algorithm, particle swarm optimization is used to improve ant colony algorithm. By comparing the optimal solution of the particle with that of the whole population, the position and speed of the individual are updated. Based on the improved ant colony algorithm, the robot with mechanical arm can carry out path planning and mechanical arm trajectory planning.

The results show that the convergence speed of the common ant colony algorithm is relatively slow; the convergence speed of the improved ant colony algorithm is relatively fast, the planned path length is short, and the average path length reaches the optimal value. There are some errors between the actual trajectory and the ideal trajectory planning of the manipulator in two-dimensional and three-dimensional space. Under the condition of random terrain and U-shaped obstacles, compared with the common ant colony algorithm, the improved ant colony algorithm can make the path planning result of robot shortest and best, and the number of optimal iterations is also greatly reduced.

There are also some deficiencies. First, the application of the improved ant colony algorithm in robot path planning is in the initial stage, and the stability and real-time performance of the algorithm need to be further verified. Second, the experiment is based on the simulation platform, and the simulation environment is ideal; however, there may be some unknown factors in the real environment that affect the operation effect of the algorithm, which needs to be verified in the follow-up study.

References

[1] Niko Sünderhauf, Brock O, Scheirer W, et al. (2018) The Limits and Potentials of Deep Learning for Robotics. The International journal of robotics research, 37(4-5), 405-420.

[2] Johnson M, Shrewsbury B, Bertrand S, et al. (2018) Team IHMC's Lessons Learned from the DARPA Robotics Challenge: Finding Data in the Rubble. Journal of Field Robotics, 34(2), 241-261.

[3] Rubenstein M, Shen W M. (2016) Regenerative patterning in Swarm Robots: mutual benefits of research in robotics and stem cell biology. International Journal of Developmental Biology, 53(5-6), 869.

[4] Ravankar A, Ravankar A A, Kobayashi Y, et al. (2016) SHP: Smooth Hypocycloidal Paths with Collision-Free and Decoupled Multi-Robot Path Planning. International Journal of Advanced Robotic Systems, 13(3), 1.

[5] Sun P, Yu Z. (2017) Tracking Control for a Cushion Robot Based on Fuzzy Path Planning With Safe Angular Velocity. IEEE/CAA Journal of Automatica Sinica, 4(04), 37-46.
[6] Kang J G, Lim D W, Choi Y S, et al. (2021) Improved RRT-Connect Algorithm Based on Triangular Inequality for Robot Path Planning. Sensors, 21(2), 333.
[7] Hernandez K, Bacca B, Posso B. (2017) Multi-goal Path Planning Autonomous System for Picking up and Delivery Tasks in Mobile Robotics. IEEE Latin America Transactions, 15(2), 232-238.
[8] Song X, Gao S, Chen C B, et al. (2018) A New Hybrid Method in Global Dynamic Path Planning of Mobile Robot. International Journal of Computers, Communications & Control (IJCCC), 13(6), 1032-1046.
[9] Pitonakova L, Crowder R, Bullock S. (2018) The Information-Cost-Reward framework for understanding robot swarm foraging. Swarm Intelligence, 12(1), 71–96.
[10] Wang G, Zhou J. (2021) Dynamic robot path planning system using neural network. Journal of Intelligent and Fuzzy Systems, 40(2), 3055-3063.
[11] Toksari M D. (2016) A hybrid algorithm of Ant Colony Optimization (ACO) and Iterated Local Search (ILS) for estimating electricity domestic consumption: Case of Turkey - ScienceDirect. International Journal of Electrical Power & Energy Systems, 78, 776-782.
[12] Chen, Yongliang, Aijun. (2016) Application of ant colony algorithm to geochemical anomaly detection. Journal of Geochemical Exploration: Journal of the Association of Exploration Geochemists, 164, 75-85.
[13] Hu H, Chen X, Zhen L, et al. (2019) The Joint quay crane scheduling and block allocation problem in container terminals. IMA Journal of Management Mathematics, 30(1), 51-75.
[14] Liao Q, Guo Y, Tu Y, et al. (2018) Fidelity-Based Ant Colony Algorithm with Q-learning of Quantum System. International Journal of Theoretical Physics, 57(3), 862-876.
[15] Tang Y, Guan X. (2017) Parameter estimation for time-delay chaotic system by particle swarm optimization. Chaos Solitons & Fractals, 40(3), 1391-1398.
[16] Gong Y J, Li J J, Zhou Y, et al. (2017) Genetic Learning Particle Swarm Optimization. IEEE Transactions on Cybernetics, 46(10), 2277-2290.
[17] Huang Y, Wang Q, Shi L, et al. (2016) Underwater gas pipeline leakage source localization by distributed fiber-optic sensing based on particle swarm optimization tuning of the support vector machine. Applied Optics, 55(2), 242.
[18] Li Q, Tsang L. (2016) Wave scattering from lossy dielectric random rough surfaces using the physics-based two-grid method in conjunction with the multilevel fast multipole method. Radio Science, 36(4), 571-583.
[19] Xie X, Fan S, Zhou X, et al. (2019) Inverse Kinematics of Manipulator Based on the Improved Differential Evolution Algorithm. Jiqiren/Robot, 41(1), 50-57.
[20] Kim J S, Jeong Y H, Park J H. (2016) A geometric approach for forward kinematics analysis of a 3-SPS/S redundant motion manipulator with an extra sensor using conformal geometric algebra. Meccanica, 51(10), 2289-2304.