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Tower crane path planning based on improved ant colony algorithm

HE Yumin[1*], HU Xiangyang[1], ZHANG Jinhua[1], YAO Shipeng[1], LIU Difang[2], MEN Xinyan[2]

1. College of Electrical & Mechanical Engineering, Xi' an University of Architecture & Technology, Xi' an 710055, China;
2. Shaanxi Construction Machinery Co., Ltd., Xi' an 710201, China

***Corresponding author:** HE Yumin (he_yumin@163.com)

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Abstract: In order to solve the problem of path planning of tower cranes, an improved ant colony algorithm was proposed. Firstly, the tower crane was simplified into a three-degree-of-freedom mechanical arm, and the D-H motion model was established to solve the forward and inverse kinematic equations. Secondly, the traditional ant colony algorithm was improved. The heuristic function was improved by introducing the distance between the optional nodes and the target point into the function. Then the transition probability was improved by introducing the security factor of surrounding points into the transition probability. In addition, the local path chunking strategy was used to optimize the local multi-inflection path and reduce the local redundant inflection points. Finally, according to the position of the hook, the kinematic inversion of the tower crane was carried out, and the variables of each joint were obtained. More specifically, compared with the traditional ant colony algorithm, the simulation results showed that improved ant colony algorithm converged faster, shortened the optimal path length, and optimized the path quality in the simple and complex environment.

Key words: tower crane; ant colony algorithm; transition probability; local path chunking strategy; path planning

0 Introduction

With the rapid development of artificial intelligence technology, the field of construction machinery is also gradually expanding the application scenarios of artificial intelligence technology[1]. In fact, tower cranes are the most used type of cranes in the construction industry. Using intelligent algorithm for tower crane path planning can provide optimal hoisting path without collision for tower crane, thus improving safety and productivity[2,3].

Currently, the implementation methods of path planning include A* algorithm[4], artificial potential field method[5,6], genetic algorithm[7], particle swarm algorithm[8], and ant colony algorithm[9], etc. Although the A* algorithm can achieve global optimum, it is less efficient due to too many search points. And the artificial potential field method has good real-time performance, but it is easy to fall into local minima. And the genetic algorithm has a slower operation speed due to the large storage space occupied by the path and the large number of iterations[10]. In addition, the ant colony algorithm has received widespread attention because of its strong robustness and adaptability. However, the traditional ant colony algorithm still has problems such as slow convergence speed, easy to fall into local optimum, and poor path quality[11].

In view of the defects of the traditional ant colony algorithm, researchers have proposed some improved ant colony algorithms. Yang et al.[12] applied the idea of A* algorithm adaptively to adjust the heuristic function according to the distance between the next node and the target point in the ant colony algorithm, and improved the state selection strategy, which sped up the convergence speed of the algorithm, but increased the possibility that the next node deviates from the search path and falls into a local optimum. Xie et al.[13] addressed the problems that the basic ant colony algorithm had low search efficiency in the early stage and went through obstacles in the process of seeking the best path. What's more, the pheromone initialization method was improved and the heuristic factor was adjusted dynamically, which effectively reduced the number of iterations to reach the optimal path in the early stage of ants, but increased the risk of the algorithm falling into a local optimum. In order to avoid the algorithm is immature or falls into local optimal, Zhao et al.[14] set the upper and lower limits of pheromone concentration and used the adaptive adjustment of volatility coefficient, which improved the convergence quality of the algorithm results, but the algorithm convergence speed was not significantly accelerated. Zhang et al.[15,16] improved the classical ant colony algorithm by using multi-stage search strategy, domain search strategy, and multi-swarm search strategy to shorten the end movement path by more than 3%.

In order to solve the problems of slow convergence speed, easy to fall into local optimum, and poor quality of planned paths of the traditional ant colony algorithm, an improved ant colony algorithm was proposed for tower crane path planning. Firstly, according to the structural characteristics of the tower crane, the mechanical arm model of the tower was established using the D-H method. The forward and inverse kinematic equations were derived, the heuristic function was improved, and the distance parameter between the next node and the target point was introduced to speed up the convergence speed of the algorithm. Besides, the state transition probability was improved by introducing the safety factor of surrounding points, which reduces the risk of the algorithm falling into the local optimum. In addition, the local path was optimized in blocks, which reduced the redundant inflection points of the local path and improved the path quality of the planning.

1 Modeling of tower crane

According to the structural characteristics and movement mode of the tower crane, it can be simplified as a mechanical arm with one rotating joint and two translating joints. In order to describe the coordinate system of each connecting rod of the tower crane and the geometric parameters between adjacent connecting rods, the D-H parameter method was proposed in 1955[17]. This method requires 4 parameters to describe the relationship among the position, orientation, and the adjacent coordinate system. One coordinate system is established for each link, and a 4×4 homogeneous matrix is used to represent the spatial position relationship between the adjacent links. Finally, the position and orientation of the end effector relative to the base coordinate system are obtained. An improved D-H method was proposed in 1986[18], which was used to consolidate the coordinate system at the proximal end of the link when establishing the joint coordinate system.

Since the coordinate system modeling method of the standard D-H method is relatively simple and straightforward, the standard D-H modeling method is used to model the kinematics of the tower crane. The established linkage coordinate system is shown in Fig. 1. The model includes three rigid links, one rotational joint, and two translating joints. The D-H parameters of the mechanical arm are shown in Table 1. Here, a_i represents the length of the common vertical line between adjacent z-axes, α_i indicates the rotation angle between adjacent z-axes, d_i denotes the distance between adjacent x-axis, and θ_i represents the rotation angle between adjacent x-axis. Since joint 1 is a rotation joint, joint 2 and joint 3 are translation joints, θ_1, d_2, d_3 are joint variables.

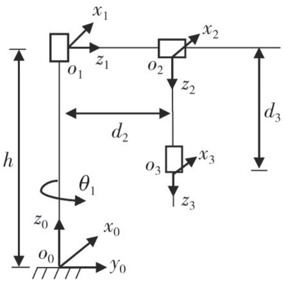


Fig. 1 D-H model of tower crane

Table 1 D-H parameters of tower crane

Connecting Rod i	a_i/m	α_i/(°)	d_i/m	θ_i/(°)
1	0	90	h	$-360\leqslant\theta_1\leqslant 360$
2	0	90	$3.85\leqslant d_2\leqslant 85$	0
3	0	0	$0\leqslant d_3\leqslant 81.8$	0

2 Kinematic analysis of tower crane

2.1 Positive kinematic analysis

The positive kinematics of the tower crane is used to determine the position of the end-effector by calculating all possible positions and attitudes of each connecting rod based on known joint angles and displacements (The position of end-effector is obtained by the product of linkage transformation). A 4×4 homogeneous transformation matrix is used to describe the position between different connecting rods. If A_1 denotes the position of the first connecting rod to the base coordinates, A_2 represents the position of the second connecting rod to the base coordinates, and A_n indicates the position of the nth connecting rod to the base coordinates, then the transformation matrix of the nth connecting rod to the base coordinate system is

$$T_n = A_1, A_2, \cdots, A_n. \tag{1}$$

The homogeneous transformation matrix of two adjacent connecting joints is

$$\begin{gathered} {}_{i-1}^{\;\;i}\boldsymbol{A} = \\ \boldsymbol{Trans}(0,0,d_i)\boldsymbol{Rot}(z_{i-1},\theta_i)\boldsymbol{Trans}(a_i,0,0)\cdot \\ \boldsymbol{Rot}(x_{i-1},\alpha_i) = \\ \begin{bmatrix} \cos\theta_i & -\sin\theta_i\cos\alpha_i & \sin\theta_i\sin\alpha_i & a_i\cos\theta_i \\ \sin\theta_i & \cos\theta_i\cos\alpha_i & -\cos\theta_i\sin\alpha_i & a_i\sin\theta_i \\ 0 & \sin\alpha_i & \cos\alpha_i & d_i \\ 0 & 0 & 0 & 1 \end{bmatrix}. \end{gathered} \tag{2}$$

From the parameters of each linkage of the tower crane model in Table 1, the position of the tower crane hook relative to the base coordinates is

$$ {}^3_0T = {}^1_0T\,{}^2_1T\,{}^3_2T = \begin{bmatrix} a_x & b_x & c_x & p_x \\ a_y & b_y & c_y & p_y \\ a_z & b_z & c_z & p_z \\ 0 & 0 & 0 & 1 \end{bmatrix}, \tag{3} $$

where a_x, a_y, a_z denote the direction of the x-axis of the coordinate system of tower crane hook in the basic coordinate system; b_x, b_y, b_z indicate the direction of the y-axis of the hook coordinate system in the basic coordinate system; c_x, c_y, c_z represent the direction of the z-axis of the hook coordinate system in the basic coordinate system; and p_x, p_y, p_z mean the coordinates of the tower crane hook in the basic coordinate system; $c_x = c_y = a_z = b_z = 0$, $a_x = \cos\theta_1$, $b_x = a_y = \sin\theta_1$, $b_y = -\cos\theta_1$, $c_z = -1$, $p_x = d_2\sin\theta_1$, $p_y = -d_2\cos\theta_1$, $p_z = h - d_3$. When the joint variables θ_1, d_2, d_3 are known, the position of the tower crane hook can be found by Eq. (3).

2.2 Inverse kinematic analysis

In contrast to the positive kinematics, the inverse kinematic analysis of a tower crane is used to obtain the variables of each joint (angles and displacements of joints) by working out the inverse solution of the positive kinematic transformation equation with the known position of the hook relative to the base coordinates. The inverse kinematic analysis of the tower crane is the core of the whole kinematic analysis, and a reasonable inverse kinematic analysis is a prerequisite to realize the path planning of the tower crane. According to the structural features of the tower crane, the method of reverse derivation was used to derive the inverse kinematic equations of the tower crane. Based on the positive kinematic equation of the tower crane, the solution of the inverse kinematic equation is finally obtained by deducing the inverse matrix several times.

The conversion equation between the hook and the basic coordinate system is

$$ {}^3_0T = {}^1_0T\,{}^2_1T\,{}^3_2T. \tag{4} $$

Both sides of the equation are simultaneously left multiplied by $\left({}^1_0T\right)^{-1}$. By using the parameters of each linkage of the tower model in Table 1, each joint variable can be calculated, and the results are

$$ \theta_1 = -\arctan\frac{p_x}{p_y}, \tag{5} $$

$$ d_2 = \sqrt{{p_x}^2 + {p_y}^2}, \tag{6} $$

$$ d_3 = h - p_z. \tag{7} $$

When p_y is equal to 0, θ_1 is equal to $\pm\frac{\pi}{2}$.

In summary, the derivation of the inverse kinematic equations for the tower crane shows that multiple solutions exist for the tower crane hook at the target point of any determined position. There will not be all the solutions because of the limitations of the relative position, rotation range, and displacement range of the tower crane itself. Therefore, it is necessary to discard the solutions that cannot reach the specified rotation angle. For the remaining solutions that can reach the definite position, they are selected according to specific rules. Usually, under the premise of satisfying the motion requirements of tower cranes, the solutions that do not satisfy the requirements are eliminated, and the group of the remaining solutions with the sum of minimum rotation angles for each joint is selected as the optimal solution.

3 Path planning based on improved ant colony algorithm

3.1 Traditional ant colony algorithm

The ant colony algorithm is a heuristic intelligence algorithm designed to simulate the principle of ant foraging.

1) Release of pheromones

The ants will release a quantitative amount of pheromone on the path they passed through when they search for food sources. The concentration of released pheromone is related to the length of the path, the shorter the length, the higher the concentration of released pheromone. And the subsequent ants can sense the concentration of pheromone released by other ants on the path they passed through.

2) Transfer of state

The ant $m\,(m = 1, 2, 3, \cdots, n)$ shifts its direction according to the concentration of pheromones on each path during its movement. The probability of denoting the movement of ant m from node i to node j at moment t is

$$ P^m_{ij}(t) = \frac{\left[\tau_{ij}(t)\right]^{\alpha}\left[\xi_{ij}(t)\right]^{\beta}}{\sum_{k\in A_m}\left[\tau_{ik}\right]^{\alpha}\left[\xi_{ik}\right]^{\beta}}, j \in A_m, \tag{8} $$

where A_m denotes the set of nodes that ant m is allowed to select in the next step at time t; $\tau_{ij}(t)$ indicates the size of the pheromone residual on the path of ant m from point i to point j at moment t; and $\xi_{ij}(t)$ represents the expectation heuristic function of moving from node i to node j at moment t; $\xi_{ij} = \frac{1}{d_{ij}}$, and d_{ij} represents the distance from node i to node j; α means the information heuristic factor; β denotes the expectation heuristic factor.

3) Volatilization and update of pheromones

When ants release pheromones, the pheromones on the path connected to each node will be volatilized gradually, and the volatilization coefficient of pheromone is represented by the parameter $\rho(0<\rho<1)$. When all ants complete a cycle, the pheromone concentration on the connection path of each node needs to be updated, and the updating process is

$$\tau_{ij}(t+1)=(1-\rho)\tau_{ij}(t)+\Delta\tau_{ij}(t), \tag{9}$$

$$\Delta\tau_{ij}(t)=\sum\nolimits_{m=1}^{n}\tau_{ij}^{m}(t), \tag{10}$$

where ρ is the pheromone volatility coefficient; $\Delta\tau_{ij}(t)$ is the pheromone increment on the path (i, j); and $\Delta\tau_{ij}^{m}(t)$ is the amount of residual pheromone of the ant m on the path (i, j).

The update method of pheromone has the three models: a) ant cycle system, b) ant quantity system, c) ant density system. The most widely used among them is ant cycle system, i.e.,

$$\Delta\tau_{ij}^{m}(t)=\frac{Q}{L_m}, \tag{11}$$

where Q is a constant that represents the total amount of pheromones released by the ant in one cycle or a segment of the path, and L_m is the length of the ant's path in this cycle.

In addition, the ant will choose the path with higher pheromone concentration with higher probability and release a quantitative amount of pheromone to enhance the pheromone concentration on that path. It will form positive feedback, and finally find the optimal path.

3.2 Improvement of ant colony algorithm

In practice, the traditional ant colony algorithm does not allow the tower crane to reach the target location quickly, and its path is always not optimal. After repeated comparisons and summaries, the reason is that the traditional ant colony algorithm initially only knows the location of the initial point and the target point, and ants search based on the pheromone residue and heuristic function. However, the pheromone concentration of each path in the initial state is the same. Therefore, it will waste a lot of time in the process of the ant's searching towards the target point. Consequently, the algorithm converges slowly. In the process of ant iteration, the paths with low pheromone concentration are gradually eliminated, and new paths are not explored enough, which will fall into the local optimum easily. Therefore, the traditional ant colony algorithm needs to be optimized.

1) Improvement of heuristic function

At the beginning of the path planning, the paths are selected based on the specified transfer probability, which relies on the information heuristic factor and the expectation heuristic factor at the next path point. The heuristic function is

$$\xi_{ij}=\frac{1}{d_{ij}}, \tag{12}$$

where d_{ij} represents the distance between node i and node j. It shows that the expected degree of ants when walking from the current node to the next node is related to the distance between the nodes. d_{ij} is a deterministic quantity that can only represent the local paths. At the early stage of path planning, there is no guarantee on the merit of the path, and it is even not possible to determine whether the hook can reach the target point. Therefore, in this paper, the distance between the next node and the target point is introduced into the heuristic function, and the heuristic function is

$$\xi_{ij}=\frac{1}{d_{ij}+\delta d_{jt}}, \tag{13}$$

where d_{ij} is the distance between node i and node j, and d_{jt} is the distance from node j to the target point, and δ is the weight of the distance from the next node to the target point. The improved heuristic function guides the ants towards the target point during the selection of the next node, which increases the effectiveness of the algorithm, improves the efficiency of the algorithm, and speeds up convergence. In order to avoid the deviation of the ant search direction from falling into the local optimum, the value of δ should be between 0 and 0.5.

2) Security factor of surrounding points

When searching with an improved heuristic function, although the convergence speed is accelerated, the ants may still deviate from the path search direction with a higher probability. In addition, for safety reasons, there is an increased risk when ants search in the direction of an obstacle. Therefore, the security factor of the surrounding points is introduced in this paper, which takes the obstacle situation near the next node into consideration. The security factor of surrounding points is

$$\omega_j=\frac{\omega_0}{\omega_s}, \tag{14}$$

where ω_0 is the number of grids occupied by obstacles near node j, and ω_s is the number of all grids near node j. Therefore, the state transition probability is

$$P_{ij}^{m}(t)=\frac{\left[\tau_{ij}(t)\right]^{\alpha}\left[\xi_{ij}(t)\right]^{\beta}\left[1-\left(\frac{\omega_0}{\omega_s}\right)\gamma\right]}{\sum_{k\in A_m}\left[\tau_{ik}\right]^{\alpha}\left[\xi_{ik}\right]^{\beta}}, j\in A_m, \tag{15}$$

where γ is the weight value of security factor of surrounding points. Since it is used as a reference and cannot be considered as the main factor, the value of γ should be between 0 and 1.

3) Optimization of path

The traditional ant colony algorithm only relies on the amount of information residuals as well as the heuristic function to search for paths, which are mainly evaluated by the path length except the pheromone residuals, thus ignoring the evaluation of good and bad local paths. In fact, the process of path planning of tower cranes often exists redundant inflection points in the local area, which greatly reduces the search efficiency of the algorithm and also affects the evaluation of the path length.

In addition, the path with multiple inflection points can also cause shock and jitter of the tower body and boom, etc. Therefore, in order to reduce the redundant inflection points, the local path chunking strategy is proposed to optimize the local path in chunks. When there is a significant deviation from the interval direction of the starting point to the target point in the next node obtained from the cost judgment calculated by the heuristic function of the improved ant colony algorithm, the point is judged to be a redundant inflection point, and the point is included in the set of forbidden search points. Then, the algorithm will go back to the previous node and search again until the next node conforms to the interval direction of the starting point and the target point.

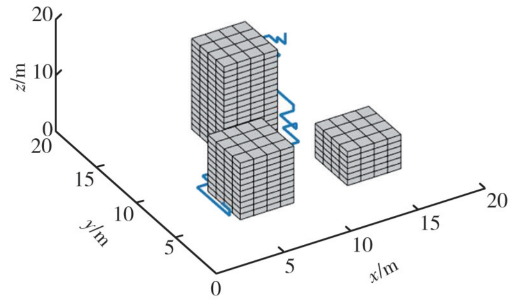
4 Simulation process and analysis

In order to verify the feasibility and effectiveness of the improved ant colony algorithm, we carried out path planning simulation on the tower crane hook in MATLAB. Then the effects of traditional ant colony algorithm and improved ant colony algorithm on path planning in simple environment and complex environment were compared, respectively.

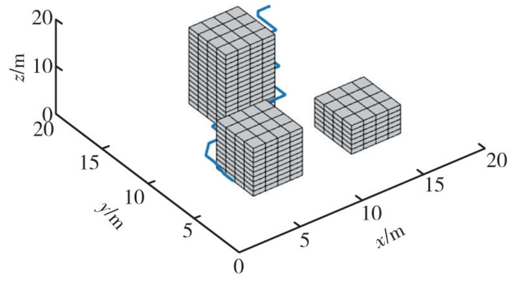
4.1 Simulation in a simple environment

We used the raster method to establish a three-dimensional raster map. The percentage of obstacles is 6.4%, and the number of discrete point divisions is 20×20×20. Besides, the coordinates of the initial point of the tower crane hook are (4, 6, 2), and the coordinates of the target point are (16, 18, 8). After many simulation experiments, the optimal simulation parameters are obtained as follows: the number of ant populations m is 50, the number of iterations is 100, the pheromone heuristic value α is 1, the fitness heuristic value β is 5, and the volatility factor ρ is 0.5. These parameters are used as input parameters of the traditional ant colony algorithm, and the output parameter is the fitness value of each iteration, which is the optimal path length of each iteration.

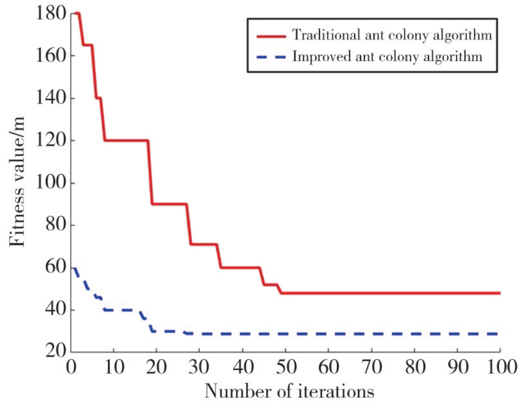
The improved ant colony algorithm introduced two additional parameters compared to the traditional ant colony algorithm, and in order to compare the path planning effect of the algorithm before and after the improvement, the other parameters were kept the same. Therefore, in addition to the above parameters, the input parameters of the improved ant colony algorithm also include the weight of security factor of surrounding point γ, and the weight of the distance of next node to the target point δ. In this paper, γ is set to 0.6, and δ is set to 0.2. After simulation experiments, the comparison of simulation results is shown in Fig.2.



(a) Path planning based on traditional ant colony algorithm



(b) Path planning based on improved ant colony algorithm



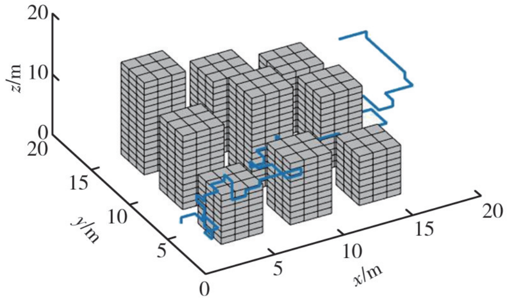
(c) Curves of fitness function

Fig. 2 Comparison of simulation results in a simple environment

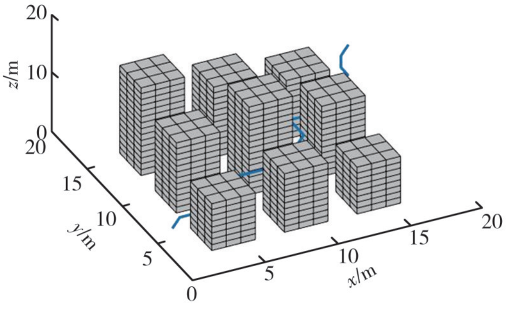
From the comparison of the fitness curves in Fig.2 (c), it can be seen that the improved ant colony algorithm converges significantly faster compared to the traditional ant colony algorithm in a simple environment. The optimal path length searched by the traditional ant colony algorithm is 48 m, while the optimal path length of the improved ant colony algorithm is 28.8 m, and the optimal path length is shortened by 40%. Compared with the traditional ant colony algorithm, the improved ant colony algorithm has significantly reduced the redundant inflection points and greatly improved the search efficiency.

4.2 Simulation in a complex environment

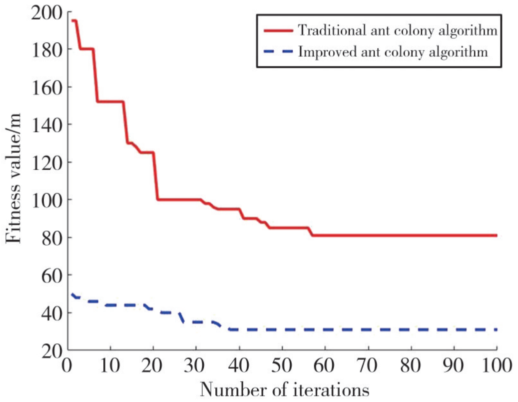
We compared the path planning effects of traditional and improved ant colony algorithms in a raster map with the obstacle percentage of 11.48%. First, some necessary parameters were introduced. The coordinates of the initial point of the tower crane hook are (1, 5, 2), and the coordinates of the target point are (18, 15, 10). In addition, the simulation parameters are as follows: the number of ant population m is 50, the number of iterations is 100, the pheromone heuristic value α is 1, the fitness heuristic value β is 6, the volatility factor ρ is 0.5. These parameters are used as input parameters of the traditional ant colony algorithm, and the output parameter is the fitness value of each iteration. The two parameters introduced in this paper are set as follows. The weight of security factor of surrounding point γ is 0.6, the weight of the distance of next node to the target point δ is 0.4. After many simulation experiments, the comparison of simulation results is shown in Fig.3.



(a) Path planning based on traditional ant colony algorithm



(b) Path planning based on improved ant colony algorithm



(c) Curves of fitness function

Fig. 3 Comparison of simulation results in a complex environment

From the comparison of the fitness curves in Fig.3(c), it can be seen that the convergence speed of the improved ant colony algorithm is significantly faster in complex environments. The optimal path length searched by the traditional ant colony algorithm is 81 m, while the optimal path length searched by the improved ant colony algorithm is 30.3 m, and the optimal path length is shortened by 62.6%. Based on the simulation results, the improved ant colony algorithm reduces a large number of redundant inflection points compared with the traditional algorithm, and greatly improves the search efficiency of the algorithm. So the improved ant colony algorithm possesses clear superiority in the convergence speed and the ability to find the optimal path.

4.3 Simulation of motion path of tower crane

The result of path planning by the improved ant colony algorithm was used as the motion path of the tower crane hook, and the motion process of the tower crane was simulated by modeling the tower crane with MATLAB Robotics Toolbox. The source codes of the model built in this paper are as follows.

```
L(1)=Link([theta1 d1 a1 alpha1]);
L(1).qlim=[-2*pi,2*pi];
L(2)=Link([0 d2 a2 alpha2]);
L(2).qlim=[0.77,30];
L(2).jointtype='P';
L(3)=Link([0 d3 a3 alpha3]);
L(3).qlim=[0,16.36];
L(3).jointtype='P';
taji=SerialLink(L,'name','taji').
```

Some joint variables of the tower crane in simple and complex environments are shown in Tables 2 and 3. Joint 1 is a rotating joint, and the angle of rotation is in radian system. The motion process of the tower crane is shown in Figs.4 and 5.

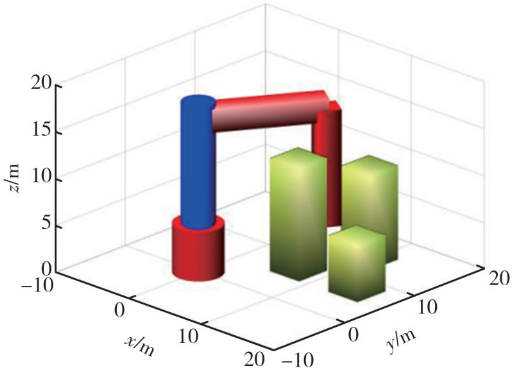
Table 2 Coordinates and joint angles of path nodes in a simple environment

Connecting Rod i	(x, y, z)	Joint 1/rad	Joint 2/m	Joint 3/m
1	(4,6,2)	2.55	7.21	14.36
2	(4,7,2)	2.62	8.06	14.36
3	(4,8,3)	2.68	8.94	13.36
4	(4,9,3)	2.72	9.85	13.36
5	(5,10,3)	2.68	11.18	13.36
6	(6,10,3)	2.60	11.66	13.36
7	(6,10,4)	2.60	11.66	12.36
8	(6,11,4)	2.64	12.53	12.36

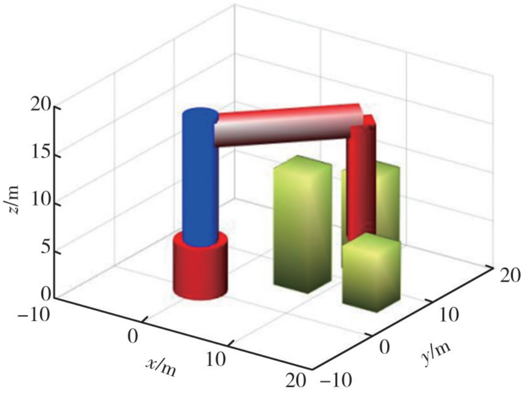
Table 3 Coordinates and joint angles of path nodes in complex environments

Connecting Rod i	(x, y, z)	Joint 1/rad	Joint 2/m	Joint 3/m
1	(1,5,2)	2.94	5.10	14.36
2	(2,6,2)	2.82	6.32	14.36
3	(3,6,2)	2.68	6.71	14.36
4	(3,6,3)	2.68	6.71	13.36
5	(4,6,3)	2.55	7.21	13.36
6	(5,6,4)	2.45	7.81	12.36
7	(6,7,4)	2.43	9.22	12.36
8	(6,7,5)	2.43	9.22	11.36

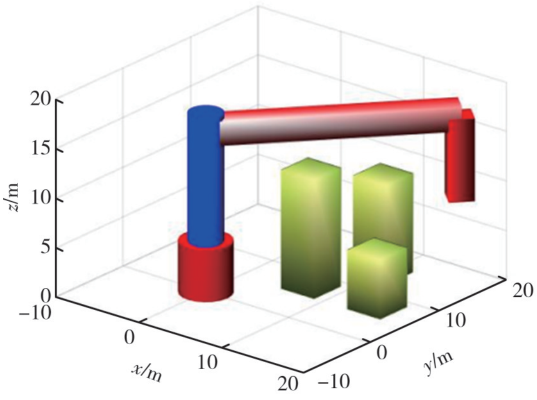
The simulation results showed that when the tower crane adopted the improved ant colony algorithm for path planning, it could find a path that met the requirements of the tower crane movement and avoided the obstacles more quickly and accurately.



(a) Starting position

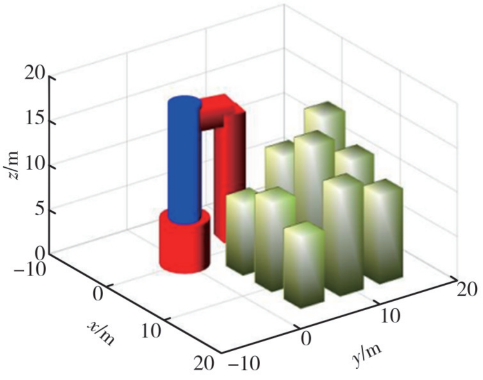


(b) Middle position

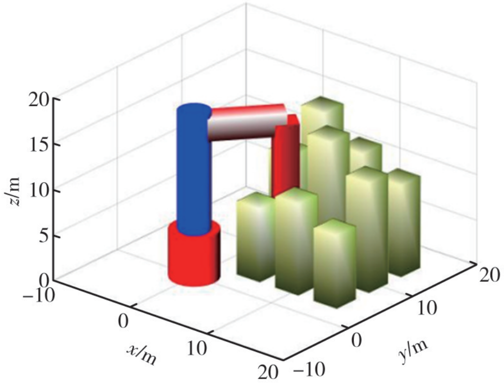


(c) End position

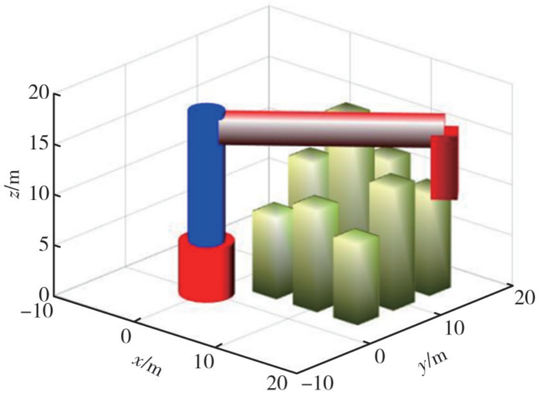
Fig. 4 Simulation process in a simple environment



(a) Starting position



(b) Middle position



(c) End position

Fig. 5 Simulation process in a complex environment

5 Conclusions

This study took tower crane as the research object, simplified it into a three-degree-of-freedom robotic arm for kinematic analysis, established the D-H kinematic model, derived the forward and inverse kinematic equations, and obtained the transformation relationship from the spatial coordinates of the tower crane hook to the variables of each joint of the tower crane. And on that basis, an improved ant colony algorithm was proposed for the path planning of the tower crane. The distance from the next node to the target point was introduced in the heuristic function and the corresponding weight parameters were set to guide the ant colony to bias the search to the target area.

The safety factor of the surrounding points was introduced in the state transfer probability to take the obstacle situation around the next node into consideration to guide the ant colony to search. The local path chunking strategy was introduced in the process of ant colony search to reduce the redundant inflection points generated in path planning. Through the simulation of path planning for tower crane hook, the results showed that the proposed improved ant colony algorithm effectively accelerated the convergence speed of the algorithm, shortened the optimal path length, and reduced the redundant inflection points. Therefore, the improved ant colony algorithm could be used to plan the safe, fast, and reasonable path for the tower crane.

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Declaration of conflicting interests

The authors have no conflict of interests related to this publication.

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基于改进蚁群算法的塔机路径规划

何育民[1*], 胡象洋[1], 张锦华[1], 姚世鹏[1], 刘帝芳[2], 门新延[2]

1. 西安建筑科技大学 机电工程学院, 陕西 西安 710055;
2. 陕西建设机械股份有限公司, 陕西 西安 710201

摘　要: 针对塔式起重机的路径规划问题，提出了一种改进蚁群算法。首先，将塔式起重机简化成一个三自由度的机械臂，建立D-H运动模型求解正、逆运动学方程。其次，对传统蚁群算法进行了改进。将可选节点与目标点的距离引入启发函数，对启发函数进行改进；在状态转移概率中引入周围点安全因素，对转移概率进行了改进；采用局部路径分块策略，对局部多拐点路径进行了优化，减少了局部冗余拐点。最后，根据吊钩的位姿对塔机进行运动学求逆，得到各关节的变量。通过在简单环境和复杂环境下塔机路径规划的仿真研究，发现提出的改进蚁群算法可加快收敛速度，缩短最优路径长度，改善路径质量。

关键词: 塔机; 蚁群算法; 转移概率; 局部路径分块策略; 路径规划

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