Intelligent obstacle avoidance path planning method for picking manipulator combined with artificial potential field method

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Abstract

Purpose – The results of obstacle avoidance path planning for the manipulator using artificial potential field (APF) method contain a large number of path nodes, which reduce the efficiency of manipulators. This paper aims to propose a new intelligent obstacle avoidance path planning method for picking robot to improve the efficiency of manipulators.

Design/methodology/approach – To improve the efficiency of the robot, this paper proposes a new intelligent obstacle avoidance path planning method for picking robot. In this method, we present a snake-tongue algorithm based on slope-type potential field and combine the snake-tongue algorithm with genetic algorithm (GA) and reinforcement learning (RL) to reduce the path length and the number of path nodes in the path planning results.

Findings – Simulation experiments were conducted with tomato string picking manipulator. The results showed that the path length is reduced from 4.1 to 2.979 m, the number of nodes is reduced from 31 to 3 and the working time of the robot is reduced from 87.35 to 37.12 s, after APF method combined with GA and RL.

Originality/value – This paper proposes a new improved method of APF, and combines it with GA and RL. The experimental results show that the new intelligent obstacle avoidance path planning method proposed in this paper is beneficial to improve the efficiency of the robotic arm.

Graphical abstract – Figure 1 According to principles of bionics, we propose a new path search method, snake-tongue algorithm, based on a slope-type potential field. At the same time, we use genetic algorithm to strengthen the ability of the artificial potential field method for path searching, so that it can complete the path searching in a variety of complex obstacle distribution situations with shorter path searching results. Reinforcement learning is used to reduce the number of path nodes, which is good for improving the efficiency of robot work. The use of genetic algorithm and reinforcement learning lays the foundation for intelligent control.

Keywords Genetic algorithm, Path planning, Reinforcement learning, Manipulator, Artificial potential field

Paper type Research paper

1. Introduction

Path planning is one of main aspects of intelligent control for manipulator. Effective path planning is of great significance in improving robotic efficiency, smoothness of motion and reducing energy consumption. Artificial potential field (APF) method is one of the most widely used obstacle avoidance path planning methods for robot, which was first proposed by Khabit. Moreover, the APF method can be applied to both static and dynamic obstacle avoidance, which has high applicability and the path planning results of the APF method are relatively smooth.

Traditional APF method sometimes traps machinery in local minima of space motion. In response to the above problem, the Rapid Exploration Random Tree algorithm can be used to detach local minima (Wang *et al.*, 2019; Chen *et al.*, 2021; Yang *et al.*, 2019). Li *et al.* (2008) used the loop search method to do path planning within an APF, i.e. to explore the lowest point of potential energy within a certain range at each node; some people set virtual target points to avoid path nodes falling into local minima through applying A-Star algorithm in APF (Sun *et al.*, 2019; Zhang *et al.*, 2017). Fuzzy Control can prevent robot falling into local minima (Zhu *et al.*, 2006; Melingui *et al.*, 2014; Han and Zhao, 2019); some people increase a virtual force of another direction to change the direction of path searching when machinery fall into local minima (Shi *et al.*, 2020; Chen *et al.*, 2018; Zhang, 2018; Cao *et al.*, 2019). These methods make up for shortcomings of traditional APF method from different perspectives, but all the results retain a large number of path nodes, which will reduce the efficiency of robot inverse kinematics analysis (Zhang *et al.*, 2018; Tsardoulias *et al.*, 2016; Hirayama *et al.*, 2019; Zhang *et al.*, 2019; Orthey *et al.*, 2018; Wang *et al.*, 2018). The agricultural picking environment is uncertain and the distribution of obstacles is disordered. The obstacle avoidance method for path planning should be able to cope with various obstacle distribution situations. In terms of

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cost, the energy consumption should be reduced while ensuring the efficiency of the robot.

In this paper, we propose a new intelligent obstacle avoidance path planning method, which consists of APF method, genetic algorithm (GA) and reinforcement learning (RL). We improve the traditional APF method and propose a new APF method based on bionic principles that can avoid falling into local minima, i.e. the snake-tongue method. Based on a slope-type potential field, snake-tongue algorithm guides the trajectory of manipulator by the height difference of potential energy in potential field with reference to hunting principles of snakes in nature. Meanwhile, GA and RL algorithms are used to reduce the path length and simplify path nodes, which is beneficial to reduce the computational volume of robot inverse kinematic analysis during path planning, so as to improve the efficiency of picking for manipulator and reduce energy consumption.

2. Intelligent obstacle avoidance method for path planning integrated with artificial potential field method

2.1 Principle of intelligent obstacle avoidance method for path planning

In case of a complex robot working environment, there are many path nodes in the result of obstacle avoidance path planning for manipulator, which reduce the efficiency of the manipulator. To improve the work efficiency of robot and reduce the energy consumption of robot, this paper proposes an intelligent obstacle avoidance method, which integrates GA and RL with APF method. The principle of the method is shown in Figure 1.

In this paper, according to principles of bionics, we propose a new path search method that can avoid falling into local minima, i.e. snake-tongue algorithm, based on a slope-type potential field. At the same time, we use GA to strengthen the ability of the APF method for path searching, so that it can complete the path searching in a variety of complex obstacle distribution situations with shorter path searching results. RL is used to reduce the number of path nodes, which is good for improving the efficiency of robot work. The use of GA and RL lays the foundation for intelligent control.

2.2 Artificial potential field method based on the improved snake-tongue method

Within the working environment of manipulator, a slope-type potential energy field is built, as shown in Figure 2.

In Figure 2(a), taking the line k connecting start point (*SP*) and target point (*TP*) as the reference, a certain range around line k is the "top of the slope." The potential energy at the "top of the slope" is the largest in the potential energy field. The farther the position is from the "top of the slope," the lower the potential energy is. The place with the largest potential energy in potential energy field is the "top of the slope," and its two

Figure 1 Principle of intelligent obstacle avoidance method for path planning integrated with artificial potential field method

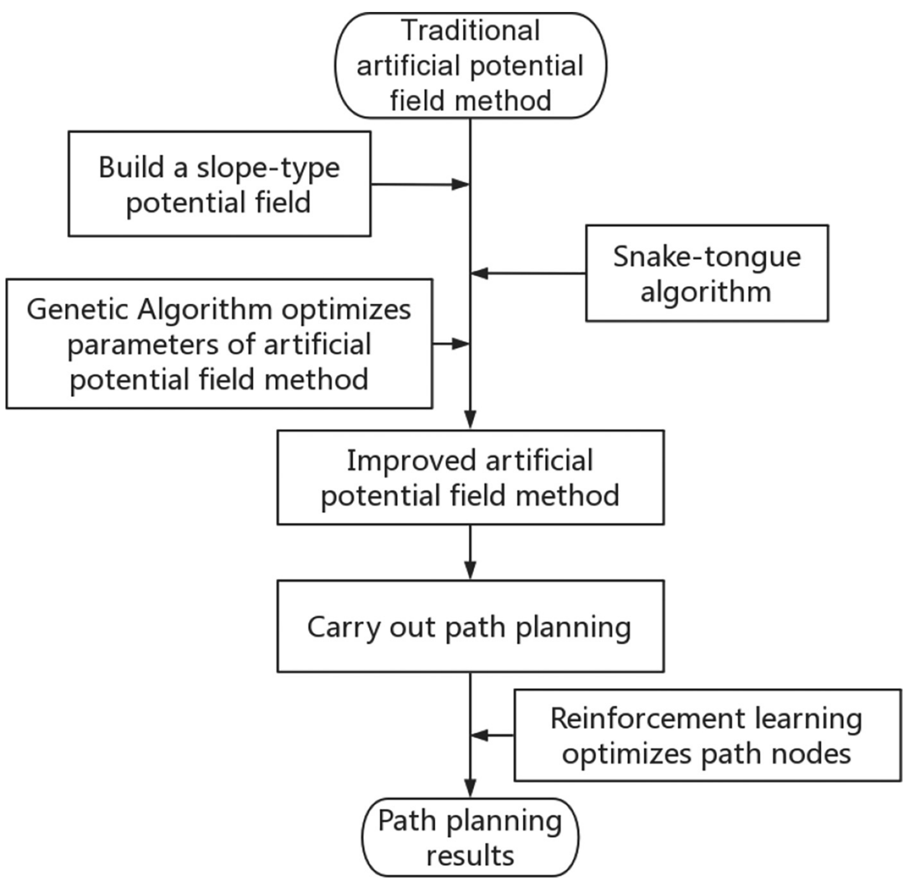

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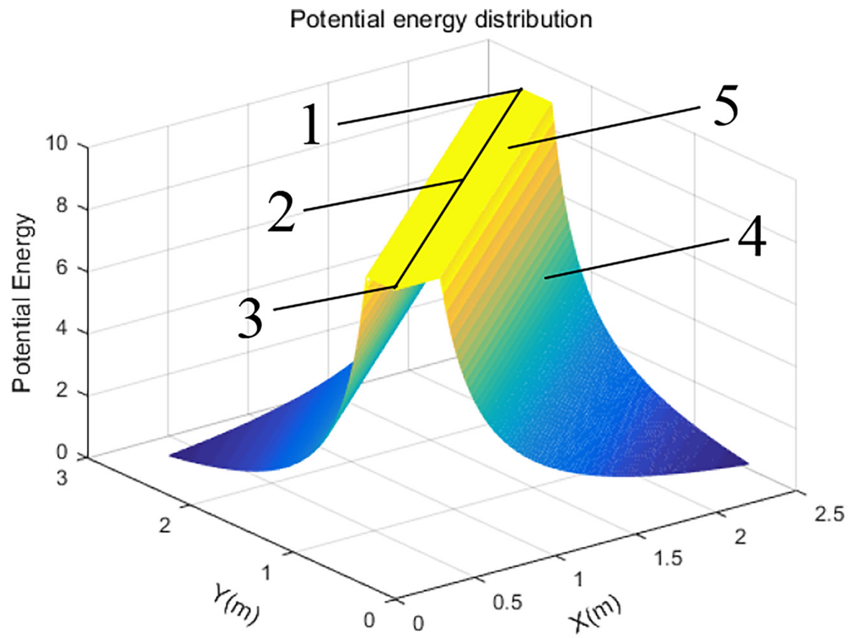
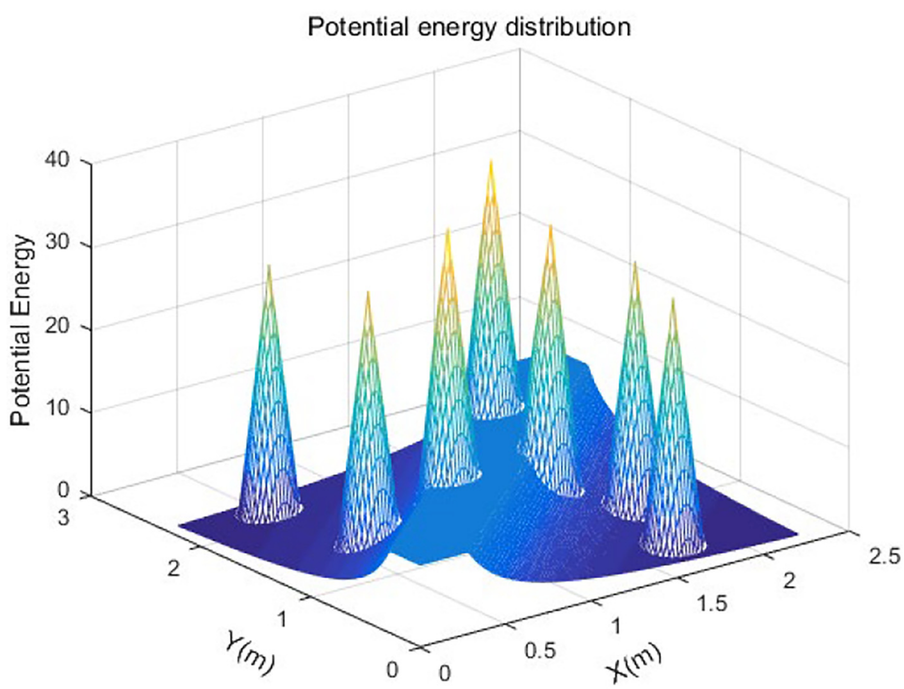
Figure 2 Slope-type artificial potential field



(a)



(b)

Notes: (a) slope-type artificial potential field (without obstacles); (b) slope-type artificial potential field (with obstacles)Target point is denoted as 1 and start point is denoted as 3; 2 represents the line *k* connecting 1 and 3; 4 represents the "slope"; 5 represents the "top of the slope."

sides are "slope." In Figure 2(b), the potential energy of the potential field is changed, when obstacles are added in the potential energy field. In practice, the positions of obstacles are mostly determined by external sensors and image processing (Ao, 2019; Wang, 2020; Ling *et al.*, 2019).

In Figure 3, the potential energy E of the node within the APF is related to d_{no_n} and d_{nk}. We define the effect of the obstacle on the node potential energy as:

$$E_{o_n} = \begin{cases} \dfrac{3M(R - d_{no_n})}{R}, & d_{no_n} < R \\ 0 \quad , & d_{no_n} \geq R \end{cases} \tag{1}$$

The potential energy at the top of the slope is M. In this paper, $M = 10$. The width of the top of the slope is *Len*. We define the effect of the potential energy field on the nodal potential energy as:

$$E_k = \begin{cases} 0 \quad , & d_{nk} < 0.5Len \\ \dfrac{0.5MLen}{d_{nk}} \quad , & d_{nk} \geq 0.5Len \end{cases} \tag{2}$$

The total potential energy of the node in the potential energy field can be expressed as:

$$E = \sum_{i=1}^{n} E_{o_n} + E_k \tag{3}$$

To cooperate with slope-type potential energy field, we propose a new path searching algorithm, that is snake-tongue algorithm based on snakes' hunting principles. The algorithm guides the trajectory of manipulator with the height difference in potential energy field, which is similar to snakes preying by smell. The principle of snake-tongue algorithm is shown in Figure 4.

Snake-tongue algorithm is divided into two parts, "snake head" and "snake tongue." At the starting point, the "snake head" searches for the position with the smallest difference between its potential energy E_1 and M on a circle with a radius of L from the starting point. The potential energy at each position on the circle is $E(\theta)$. The difference between E and M is Δ:

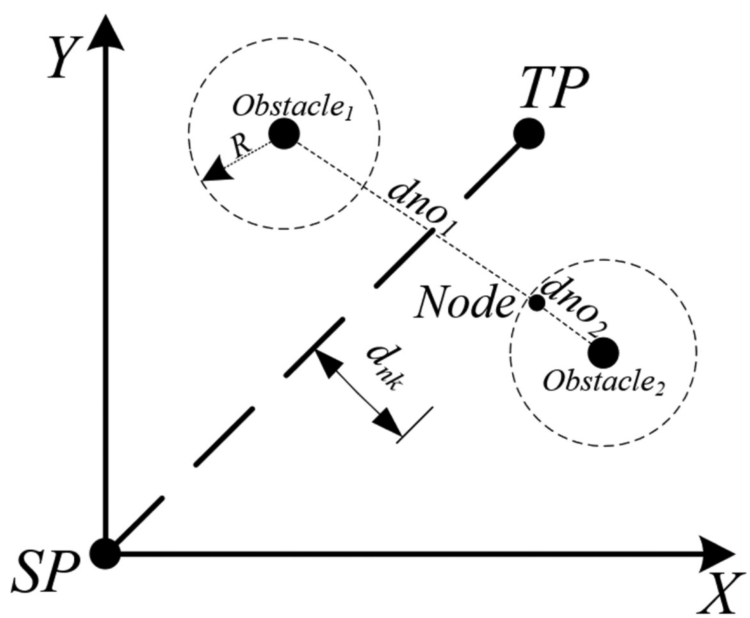
$$\Delta_1 = |E_1 - M| = \min\{|E(\theta) - M|\}, \quad \theta \in [0, 2\ \pi] \tag{4}$$

From the starting point, the "snake head" reaches that location and takes the direction of the line connecting the starting point and that position as its orientation. Suppose the coordinates of the snake head are N_{sh} (x_{sh}, y_{sh}) and the angle between the orientation of the snake head and the horizontal direction is α. Taking the direction of "snake head" as the bisector, "snake tongue" extends symmetrically on both sides of the bisector, and the bifurcation angle of "snake tongue" changes adaptively within a certain range. The angle of the snake tongue is β. The "snake tongue" is virtual and aims to explore the next movement direction for the snake head. In Figure 4(b), the positions of "snake tongue" are set as P_1 and P_2, respectively.

$$\begin{cases} P_1 = (x_{sh} + L\cos(\alpha + 0.5\beta), y_{sh} + L\sin(\alpha + 0.5\beta)) \\ P_2 = (x_{sh} + L\cos(\alpha - 0.5\beta), y_{sh} + L\sin(\alpha - 0.5\beta)) \end{cases} \tag{5}$$

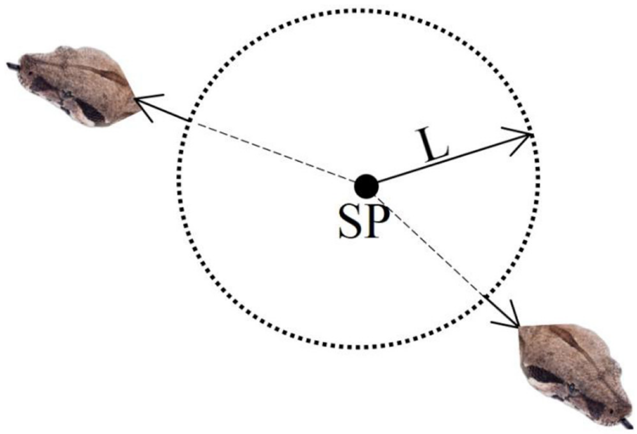
The potential energy at P_1 is E_{P_1} and the potential energy at P_2 is E_{P_2}.

Figure 3 Change in potential energy of the node within the potential energy field

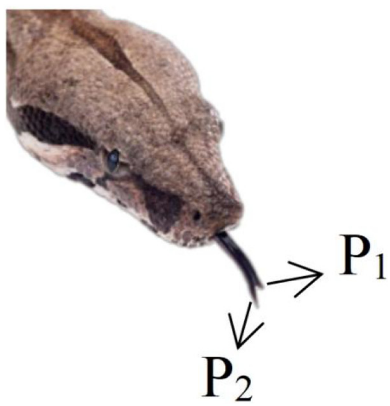


Notes: The distance between the node and the obstacle d_{no_n}. The distance between the node and the line k is d_{nk}. The obstacle potential energy field radius is R

Figure 4 Principle of snake-tongue algorithm



(a)



(b)

Notes: (a) Snake head; (b) snake tongue ; the length of the parameter L is equal to that of "snake tongue." P_1 and P_2 represent the positions of "snake tongue."

$$\Delta_{P_1} = |E_{P_1} - M| \tag{6}$$

$$\Delta_{P_2} = |E_{P_2} - M| \tag{7}$$

The position whose potential energy is more similar to that of line k is taken as the forward direction of "snake head." The next path node is N_{next}. For example, the potential energy at P_1 is closer to the potential energy of line k than that at P_2. Then "snake head" arrives at P_1 from previous position and extends "snake tongue" from P_1. During the path searching, the distance between "snake head" and each obstacle is greater than 0.1 m. This process will be repeated until the target point is reached. The process can be expressed as:

$$N_{next} = \begin{cases} P_1 \ , \ \Delta_{P_2} \geq \Delta_{P_1} \& d_{no_n} \geq 0.1, \\ P_2 \ , \ \Delta_{P_1} \geq \Delta_{P_2} \& d_{no_n} \geq 0.1, \end{cases} n = 1, \quad 2, \quad \ldots, \quad \text{n} \tag{8}$$

This method can avoid the appearance of local minima. The process of snake-tongue algorithm is shown in Figure 5.

2.3 Genetic algorithm optimizing parameters of artificial potential field method

GA is an intelligent control algorithm based on biogenetics, which solves the optimal solution of complex and combinatorial optimization problems by simulating evolutionary process of organisms in nature. GA is generally used in path planning for overall path optimization (Aghda and Mirfakhraei, 2020; Katoch *et al.*, 2021; Dener *et al.*, 2011; Chen and Gao, 2020; Lee and Kim, 2016). Some parameters in APF method are often set based on personal technical experience. However, in actual agricultural production environments, the growth density and status of fruit plants vary greatly depending on its own species and growing environments. Therefore, the same algorithm may obtain different results because of differences in work objects and environments. To reduce influences of subjective factors in the algorithm and make APF method adapt to different obstacle distributions, GA was used to optimize the parameters of APF method. The adaptation degree of different parameter combinations is calculated by GA. The goal of the method is to search the most suitable parameter combination for the environment and enable the manipulator to reach target point with a shorter path. The flow chart of GA optimizing parameters of APF method is shown in Figure 6.

In Figure 6, we set the number of individuals in the population as n and the number of the reproduction as G. Then we generate a population of number n and evaluate the fitness of individuals in the population. Selecting m obstacle distribution environments randomly, the individuals of the population are put into these environments. By APF method, m planned paths are obtained, and the sum of path lengths is used as scoring criterion of adaptation. The individuals with highest scoring during the experiment are selected as parents. The parents generate offspring through crossover and mutation, by using binary coding or float-encoding to simulate crossover and mutation of chromosomes in the process of biological evolution. Repeat this way to get the most suitable individual (e.g. the most-valued search of function).

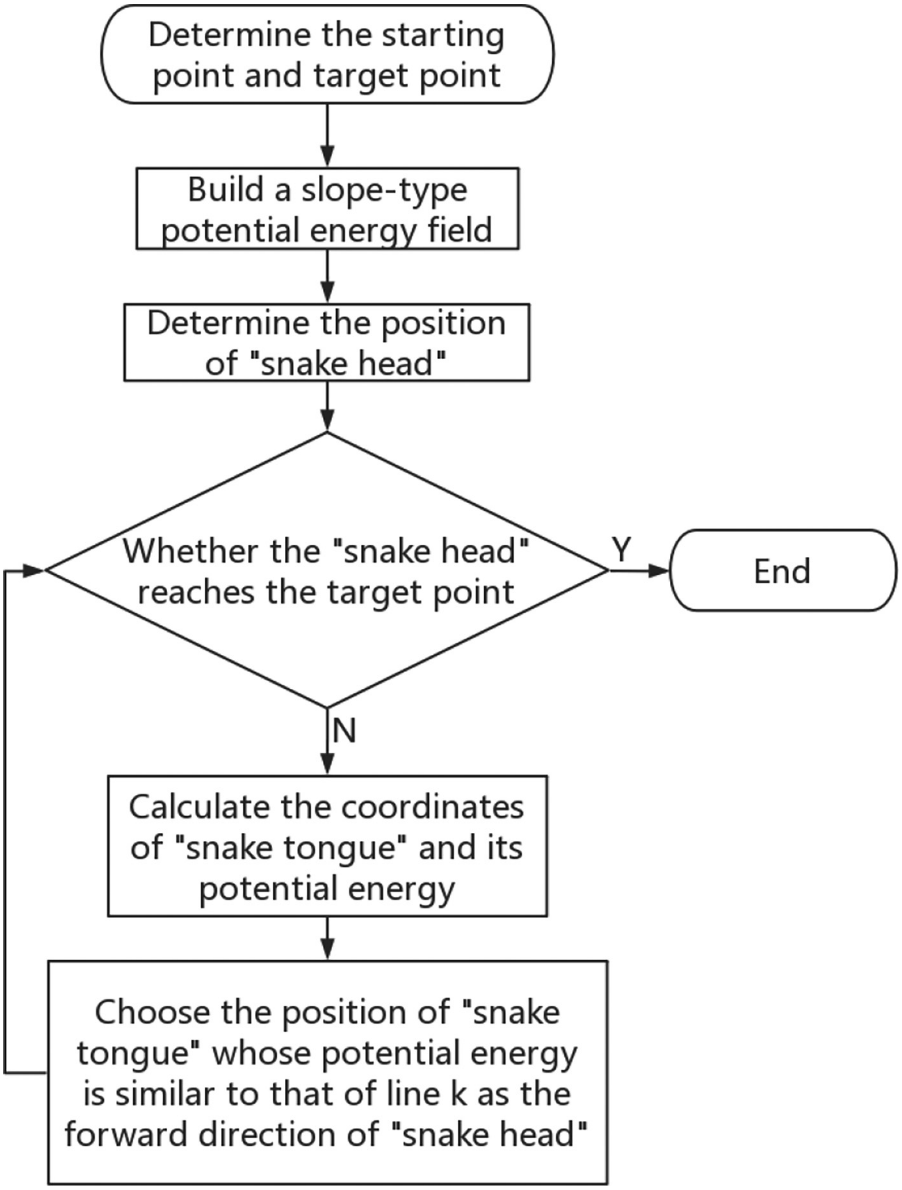
The methods of selecting parents include roulette wheel selection, stochastic tournament, excepted value selection and optimal preservation method. In this paper, we select optimal preservation method, which can ensure that the optimal individuals will not be lost during crossover and mutation. Setting floating crossover probability and variation probability can avoid the result falling into local minima, that is, most of the offspring evolve from same parents (Fadel *et al.*, 2021).

2.4 Reinforcement learning of optimizing path

RL, as an intelligent control algorithm, relies on a large amount of prior experience, i.e. the algorithm is able to learn from previous experiences and uses them as a basis for making next judgment (Li *et al.*, 2021; Liu *et al.*, 2018; Jonsson, 2019). The human-set evaluation mechanism can facilitate the algorithm's computing results to be more in line with the designer's expectations. After a certain number of iterations, a large amount of prior experience helps it make better choices, such as maze walking and path searching.

The result of the APF method contains a large number of path nodes, which reduces the computational speed of robotic inverse kinematics analysis. This paper uses RL to simplify path nodes, which is helpful to improve the efficiency of robotic work.

Figure 5 Artificial potential field method based on snake-tongue algorithm



Q-Learning and Sarsa, as two basic algorithms of RL, both essentially search for elements within an established table according to certain rules and continuously update the values within their own tables during the search process (Jang *et al.*, 2019; Jiang *et al.*, 2019; Mishra *et al.*, 2020). The rows and columns of the table represent the current state *S* of the algorithm and the next state *S_*, which will be chosen by the algorithm. The table is shown in Table 1.

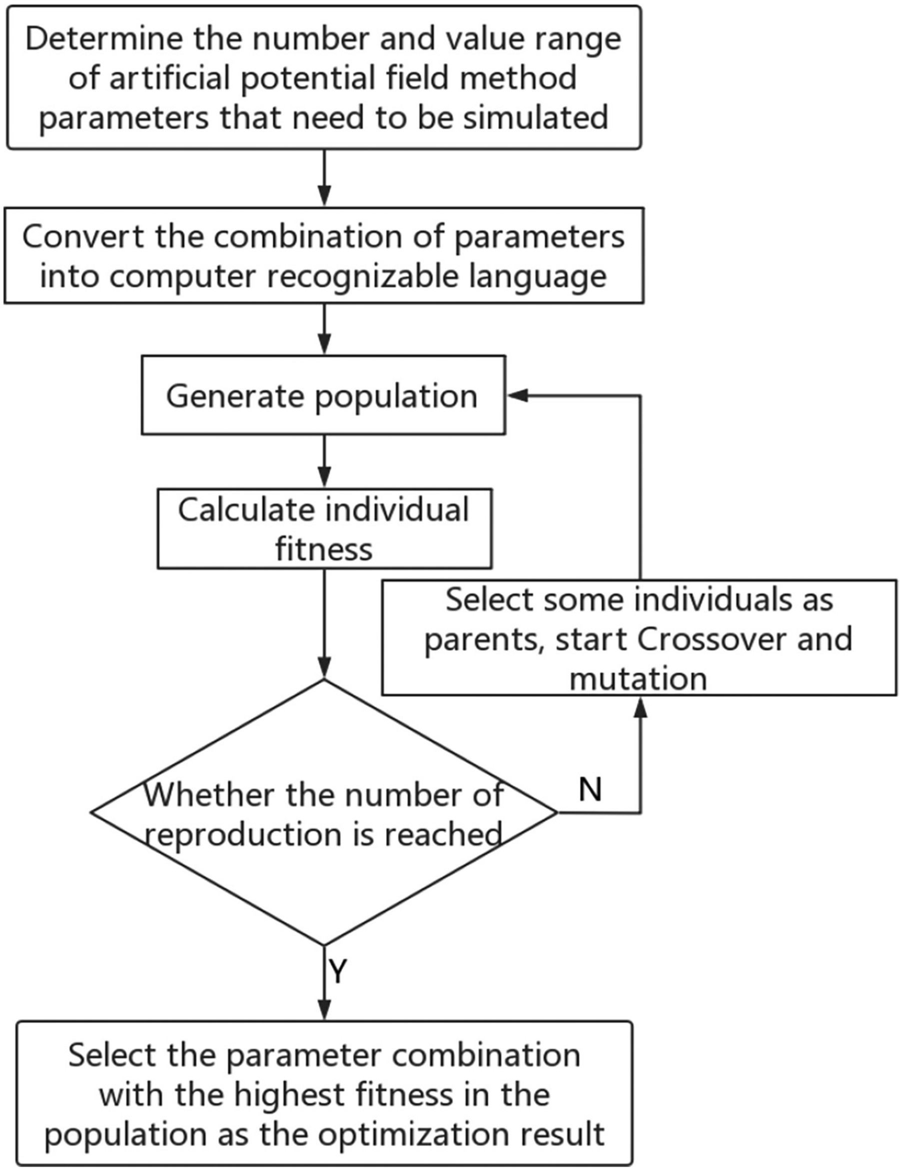
In Table 1, we suppose the current state of the algorithm is *t*, and the previous state is *c*. The algorithm selects *&* as the next state according to its previous experience and updates its own current value at (*c*, *t*) according to evaluation mechanism and the value at (*t*, *&*). After that, the state of the algorithm changes from *t* to *&*. Then the algorithm will select the next state according to its previous experience, and update the value at (*t*, *&*). RL can obtain the best selection strategy, through a certain number of iterations. Q-Learning chooses the state of the maximum value in *S* row, whereas Sarsa selects the state by converting values in *S* row into corresponding probabilities. In this paper, we use the Q-Learning algorithm, and the flowchart of RL simplifying path nodes is shown in Figure 7.

In Figure 7, we use RL to filter out some unnecessary path nodes. It is useful to reduce the computational effort of inverse kinematic analysis and improve the efficiency of manipulator.

3. Simulation experiments of intelligent obstacle avoidance path planning integrated with artificial potential field method

To verify the effectiveness of intelligent obstacle avoidance path planning method, this paper simulates the obstacle avoidance path planning of tomato string picking manipulator.

Figure 6 Genetic algorithm optimizing parameters of artificial potential field method



Set the robot end-effector starting point as *SP* (0,0), the target point as *TP* (2 ± 0.05, 2 ± 0.05), and assume the surrounding obstacle density is 7, i.e. the number of obstacles in simulation environment is 7. We observe the obstacle avoidance path planning of robot under different obstacle distributions by changing the parameter combination of APF method, which is not combined with GA or RL. The simulation results are shown in Figure 8.

As can be seen from Figure 8, the path planning results are affected by the changes of step distance (L), obstacle potential field radius (R) and slope top width (Len). The APF method with parameter variation can still complete the obstacle avoidance path planning of manipulator. However, in Figure 8(c), the changes of parameters make the APF method appear as a circular path in face of some obstacle distribution situations. The phenomenon is partly caused by too small L value. The path length of the APF method with unreasonable parameters is much longer than that of the APF method with reasonable parameters. To solve the problem, this paper will integrate APF method with GA.

Optimize the above three parameters by GA and set the variation range of three parameters: step distance ($0.01\ \text{m} \leq L \leq 0.2\ \text{m}$), radius of obstacle potential field ($0.15\ \text{m} \leq R \leq 0.3\ \text{m}$) and slope top width ($0.15\ \text{m} \leq Len \leq 0.3\ \text{m}$). The upper limit of step distance should not be too high. We can produce more data combinations and avoid missing better data combinations by increasing the number of populations or reproduction times of GA. Through the scoring system, the data combination with the highest adaptability can be selected out. When the number of the reproduction is 60, 80, 100 and 120, the results are shown in Table 2.

In Table 2, when the number of the reproduction reaches about 80, GA has tended to converge. Two sets of data emerged from the experiment, when the number of the

Table 1 Reinforcement learning table

			S_		
S	...	***t***	...	**&**	...
c	-	(*c*, *t*)	-	-	-
⋮	-	-	-	-	-
t	-	-	-	(*t*, &)	-
⋮	-	-	-	-	-
&	-	-	-	-	-
⋮	-	-	-	-	-

Notes: *S* represents the current state. *S_* represents the next state, which will be chosen by the algorithm

reproduction reached about 120. To obtain a better convergence situation, you can try to increase *m*, which represents the number of obstacle distribution environments.

In Figure 9, the APF method optimized by GA is able to complete the path planning without circular paths in the face of the obstacle distribution in Figure 8(c).

The obstacle distribution case in Figure 8(c) belongs to a special case, that is, the target point is very close to the obstacle. Because of this, we choose the more general obstacle distribution case in Figure 8(a) as the object of analysis. Taking the distribution of obstacles in Figure 8(a) as an example, we analyze the influence of GA on path planning, as shown in Figure 10(a) and 10(b). At the same time, the influence of RL on the path planning is shown in Figure 10(c).

From Figure 10(a) and 10(b), it can be seen that the path length is reduced from 4.1 to 3.269 m and the number of path nodes is also reduced from 41 to 18, after parameter optimization. Taking the above as an example, the most suitable parameter combination for the environment can be found out by GA when the working environment of manipulator has changed, after collecting the environmental information and setting the range of parameters.

Figure 7 Reinforcement learning simplifying path nodes

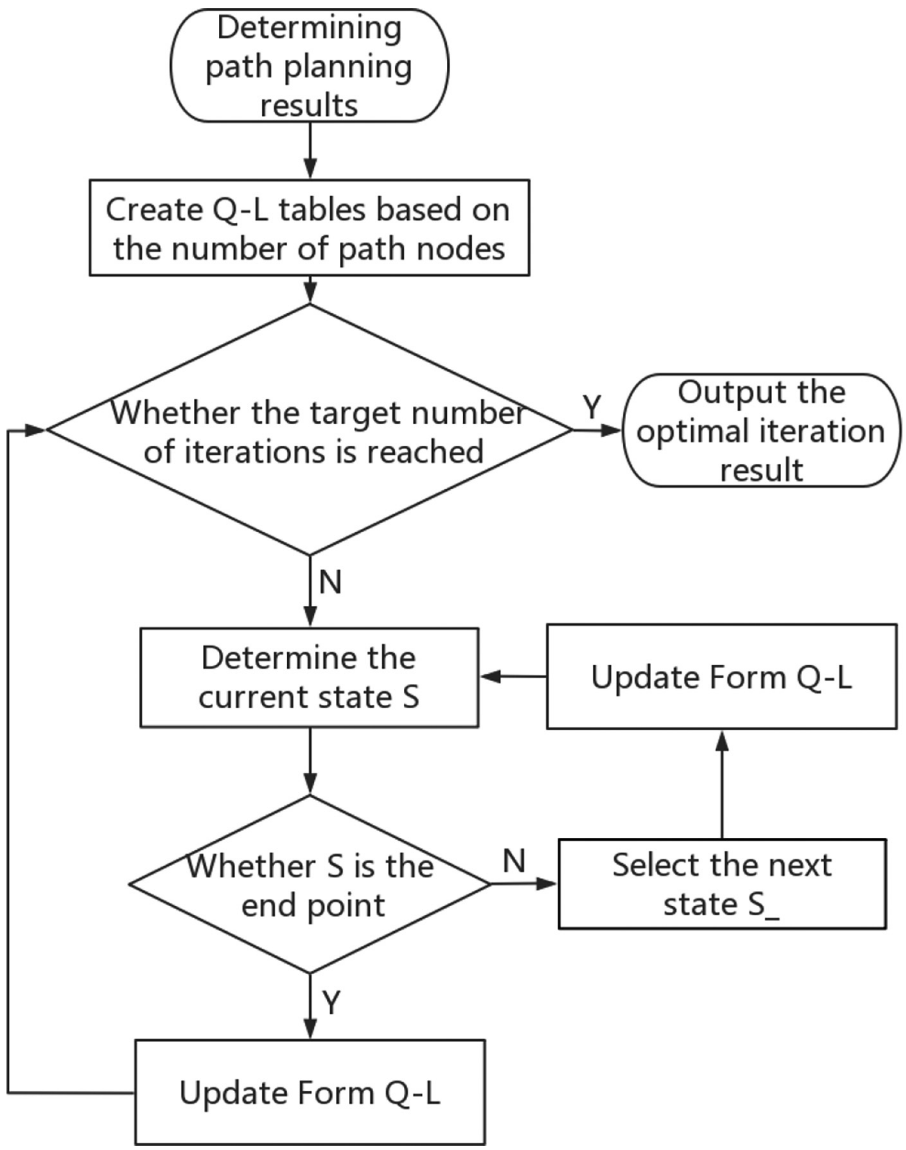
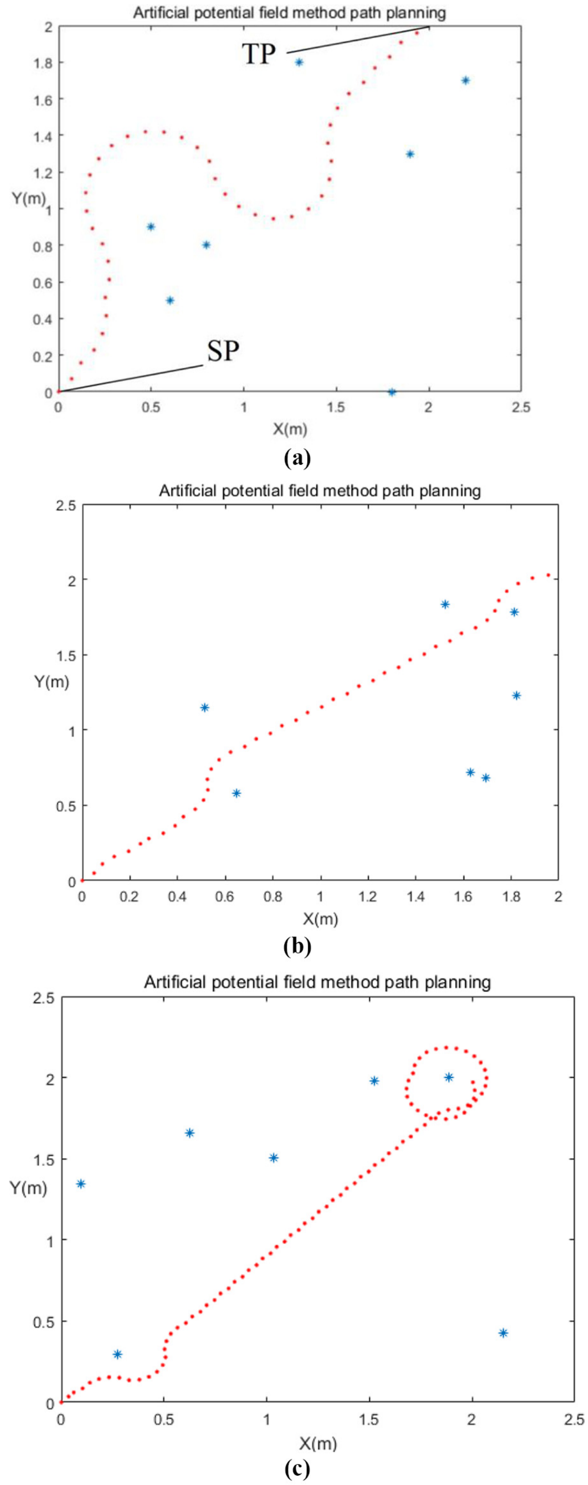


Figure 8 Path planning of artificial potential field method based on snake-tongue method



Notes: (a) *L*:0.1m, *R*:0.4m, *Len*:0.158m; (b) *L*:0.07m, *R*:0.12m, *Len*:0.2m; (c) *L*:0.05m, *R*:0.2m, *Len*:0.2m; Step distance is denoted as *L* and radius of obstacle potential field is denoted as *R*. *Len* represents the width of slope top. Obstacles are denoted as “*”. Path nodes are denoted as “.”

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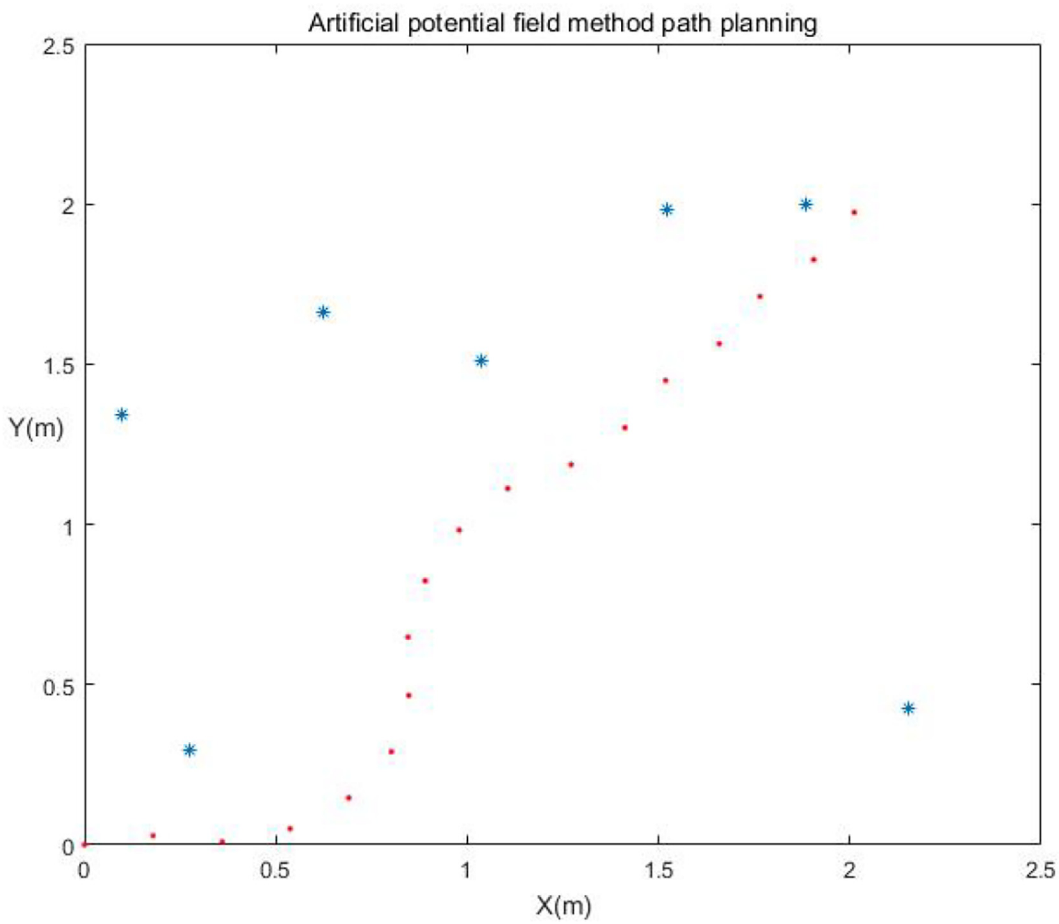
Table 2 Calculation results of genetic algorithm with different reproduction times

Number of reproduction	Calculation time (s)	Highest score	(*L*, *R*, *Len*) (m)
60	394.35	1,233.3	0.01, 0.23, 0.22
80	499.85	1,233.7	0.1816, 0.3, 0.22
100	672.44	1,233.7	0.1816, 0.3, 0.22
120	807.92	1,233.7	0.1816, 0.3, 0.22; 0.1816, 0.3, 0.24

Figure 9 *L*: 0.1816 m, *R*: 0.3 m, *Len*: 0.22 m



With the help of RL, the path length is again reduced from 3.269 to 2.979 m and the number of path nodes is reduced from 18 to 3.

4. Robot path planning experiment

A self-designed 7-degrees of freedom (DOF) manipulator is used to verify the intelligent obstacle avoidance path planning method, in this paper. The structure diagram of the robotic arm is shown in Figure 11.

Unlike outdoors, tomatoes in the trellis climb and wrap around special shelves, which themselves are more fixed and less likely to be disturbed. Moreover, the stems of tomatoes are soft and mostly fall vertically, the collision between the stem and the robot arm will not affect the movement of the robot arm. Because we use the robotic arm in Figure 11, the robotic arm does not get entangled with the stem during picking.

The robotic arm contains two moving joints and five revolving joints. This paper uses inverse kinematics analysis to solve the variation of each joint of the manipulator and substitutes it into positive kinematics for verification. Taking the front end of the end effector as the coordinate origin, the initial pose and target pose are shown in Figures 12 and 13, respectively.

According to the structural characteristics of the robotic arm, its joints 3, 4 and 5 are rotating joints in the same orientation. This experiment focuses on analyzing and comparing the working time required by the robotic arm to complete the paths in Figure 10(a)–(c).

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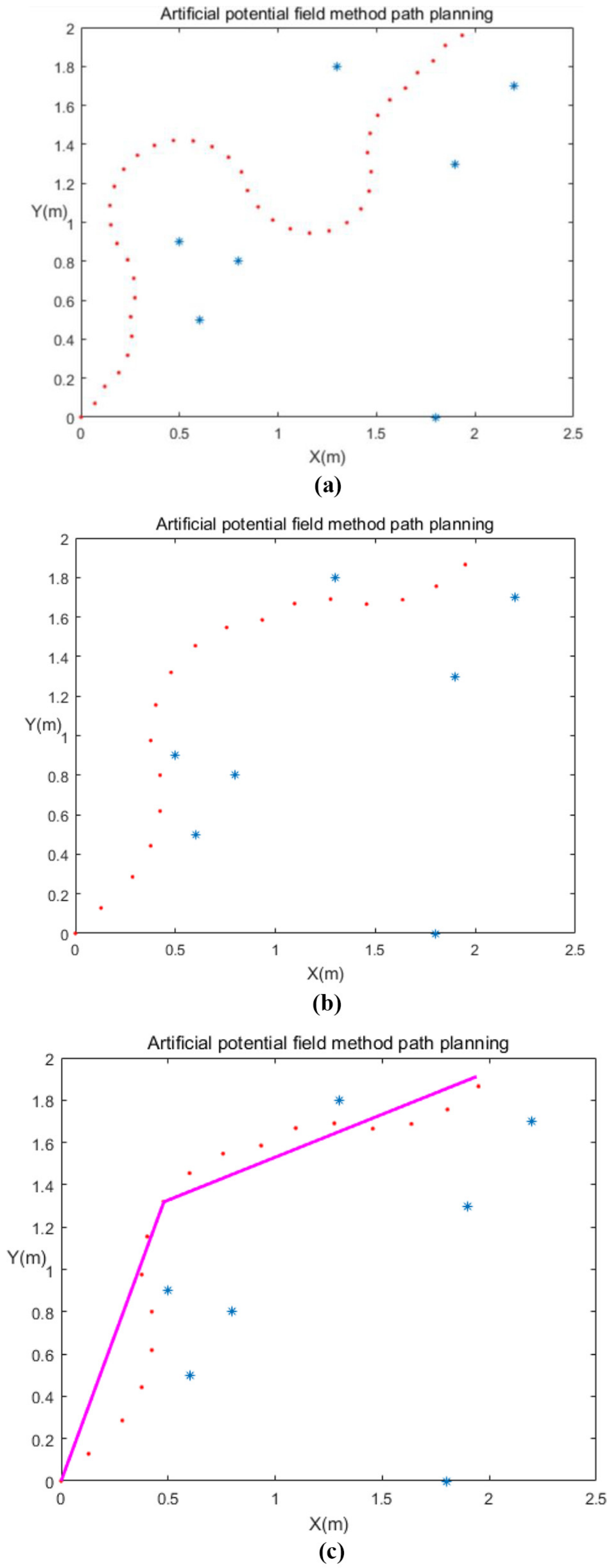
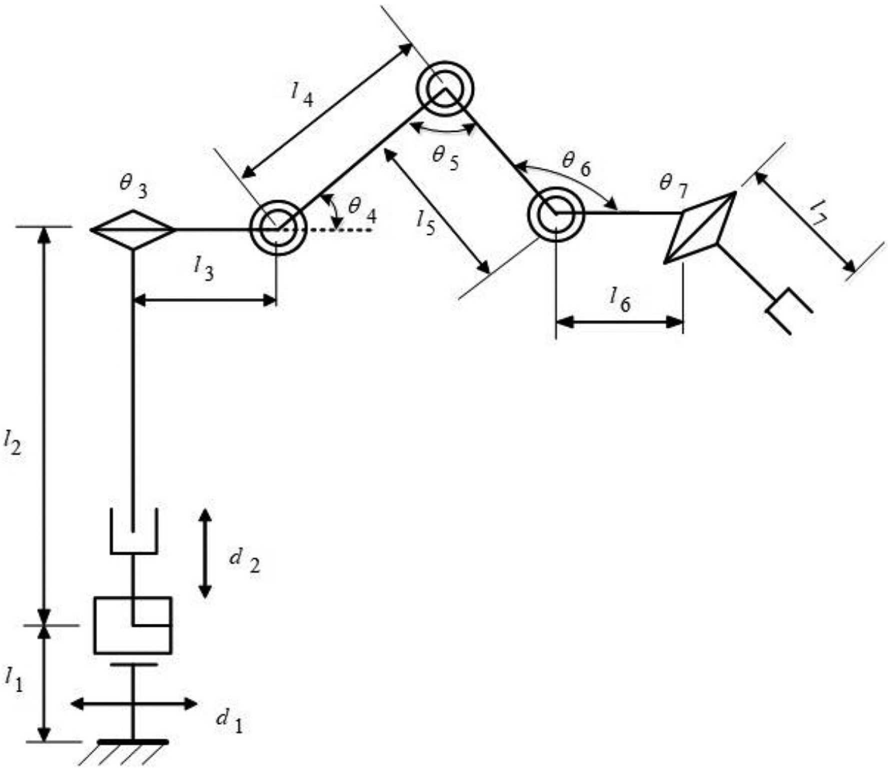
Figure 10 Artificial potential field method is sequentially integrated with genetic algorithm and reinforcement learning



Notes: (a) Before genetic algorithm optimizing parameters; (b) after genetic algorithm optimizing parameters; (c) reinforcement learning optimization results

Figure 11 Structure diagram of 7-DOF manipulator



Thanks to the inverse kinematic analysis, we can calculate the movement angle of each joint of the robot arm. Through the coordinates of the target point in the workspace, the changes of joints 1, 2 and 3 can be calculated. The amount of variation of joints 4, 5 and 6 can be found by first fixing the angle of one joint and then by a system of equations. According to the growth direction of fruit rhizome, the change of joint 7 can be obtained. The method of inverse kinematic analysis of the robotic arm in Figure 11 is described in Figure 14.

The transformation matrix of the robotic arm 4 by 4 is known to be T. The value of T (1,4) is equal to the X-coordinate of the target node in the XOY coordinate system, and the value of T (3,4) is equal to the Z-coordinate of the target node in the XOY coordinate system. Suppose the coordinates of node N are (x_n, y_n, z_n). When the distance between the node and O' is less than r', i.e. $x_n{}^2 + (y_n + d_{OO'})^2 < r'^2$, the inverse kinematic analysis of the robotic arm is shown in equations (9) and (10).

$$\begin{cases} d_1 = 0 \\ d_2 = z_n - z_{O'} \\ \theta_3 = arctan\left(\dfrac{y_n + d_{OO'} - d_1}{x_n}\right) - \pi/4 \end{cases} \tag{9}$$

$$\begin{cases} \theta_4 = 3\pi/4 - m\pi/36, \ m = 0, \ 1, \ldots 27 \\ T(1,4) = x_n \\ T(3,4) = z_n \end{cases} \tag{10}$$

In equation (10), if the equation has no solution when $m = 0$, m is increased by 1 and the equation continues to be solved, and this process continues until the equation has a solution. When the distance between the node and O' is greater than or equal to r', i.e. $x_n{}^2 + (y_n + d_{OO'})^2 \geq r'$ 2, the inverse kinematic analysis of the robotic arm is shown in equation (11).

$$\begin{cases} d_1 = y_n - y_n{}' \\ d_2 = z_n - z_{O'} \\ \theta_3 = arctan\left(\dfrac{y_n + d_{OO'} - d_1}{x_n}\right) - \pi/4 \\ \theta_4 = \theta_{4r'} \\ \theta_5 = \theta_{5r'} \\ \theta_6 = \theta_{6r'} \end{cases} \tag{11}$$

In MATLAB, this method is used for inverse kinematics analysis of nodes in Figure 10(a)–(c), and the time required is 787.78, 535.64 and 403.24 s, respectively. Compared with the calculation time required for the inverse kinematics of Figure 10(a), that of Figure 10(c) is reduced by 48.813%.

This article uses single-chip microcomputer and wifi module to realize the motion control of the manipulator. The angle calculated by inverse kinematics is sent to the wifi module through the mobile phone. After the single-chip microcomputer reads the data received by the wifi module, it controls the joint rotation of the mechanical arm. Three paths are experimented five times each, and the average of the five test results was taken. The flow chart is shown in Figure 15. During experiments, these joints did not collide with other joints within their respective joint variations.

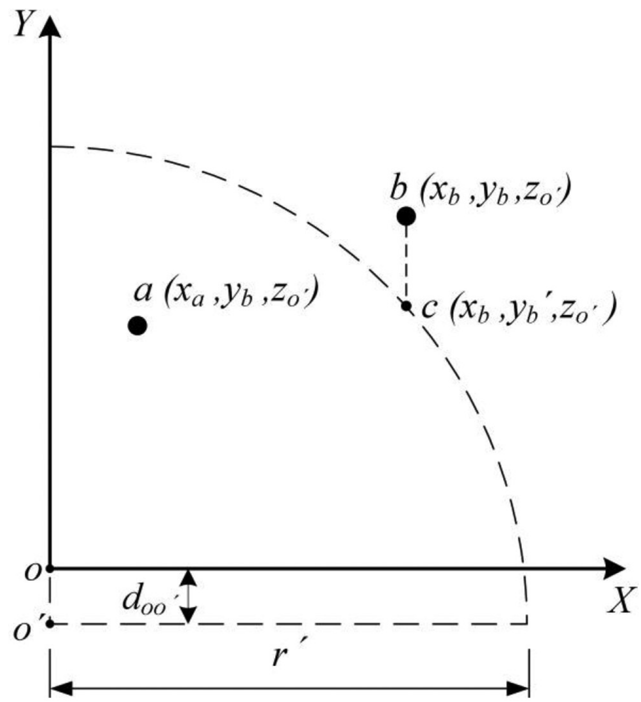
Figure 12 Initial pose of 7-DOF manipulator

Notes: d_1: 0, d_2: 0, θ_3: 0, θ_4: $3\pi/4$, θ_5: $\pi/4$, θ_6: $3\pi/2$, θ_7: 0

In Table 3, the number of path nodes is reduced from 41 to 3 by 92.683%, and the path length is reduced from 4.1 to 2.979 m by 27.341%. The average value of the working time required for the robotic arm to complete the path is 87.35, 60.08 and 37.12 s. Compared with the working time required for the path in Figure 10(a), that for the path in Figure 10(c) is reduced by 57.504%. At the same time, during many tests, the end effector of the manipulator can avoid the obstacles. This experiment verifies that the intelligent obstacle avoidance path planning method is helpful to improve the work efficiency of the robotic arm.

Figure 13 Target pose of 7-DOF manipulator

Figure 14 Schematic diagram of inverse kinematic analysis



Notes: Point O is the center of the end-effector at the initial position of the robotic arm, and O' is the center of rotation of joint 3, which are $d_{oo'}$ apart. The maximum working radius of the robotic arm is r'. Point b intersects the working space of the robotic arm along the negative direction of the Y-axis at point c. When the robotic arm reaches the maximum working radius, the angles of joints 4–6 are θ_{4r}', θ_{5r}' and θ_{6r}', respectively

5. Conclusion

1. Slope-type potential field is built based on the distribution of fruits and obstacles. Snake-tongue method is presented to solve the problem that traditional APF method sometimes makes manipulator fall into local minima of spatial motion.
2. In the intelligent obstacle avoidance path planning method proposed in this paper, the GA is only used initially to determine the parameters of the APF method, a process that takes a relatively long time. The subsequent path planning is done by the APF method and RL, and the process takes only a few seconds.
3. We use GA to strengthen the ability of APF method for path searching, so that it can complete the path searching in a variety of complex obstacle distribution situations with shorter path searching results. RL is used to reduce the number of path nodes, which is good for improving the efficiency of robot work. The use of GA and RL lays the foundation for intelligent control.
4. Compared with the ordinary APF method, intelligent obstacle avoidance algorithm, i.e. the APF method which integrates GA and RL, can reduce path length of obstacle avoiding from 4.1 to 2.979 m. The number of path nodes is reduced from 41 to 3. The working time of the robot is also reduced from 87.35 to 37.12 s. These results indicate that the intelligent algorithm proposed in this article is helpful for reducing the energy consumption of manipulator and improving the efficiency of picking manipulator.

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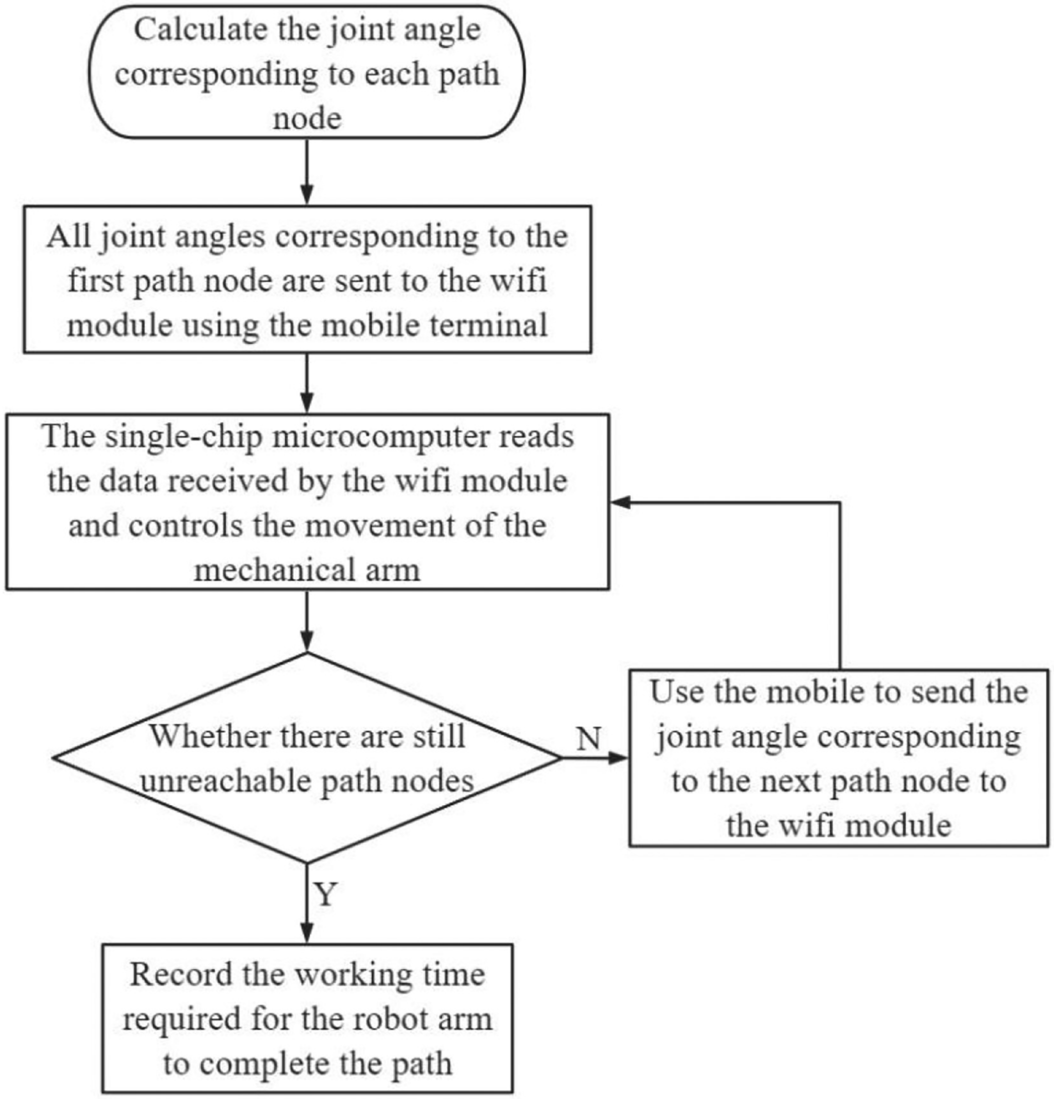
Figure 15 Using single-chip microcomputer and wifi module to realize the motion control of manipulator



5 This paper combines path planning methods with GA and RL to simplify paths can provide a reference for other path planning methods, especially when the target point is far from the starting point or the surrounding environment is complex.
6 It is necessary to further verify the effect of the intelligent obstacle avoidance algorithm applied to the actual system.

Highlights

- Snake-tongue algorithm was proposed for obstacle avoidance path planning, with reference to snake's hunting principle.
- Genetic algorithm was used to optimize parameters of artificial potential field method.
- Reinforcement learning was used to simplify path nodes of obstacle avoidance path planning.

Table 3 Time required for the robotic arm to complete the path

Path planning method	Snake-tongue method	Snake-tongue method combined with GA	Snake-tongue method combined with GA and RL
Number of path nodes	41	18	3
Path length (*m*)	4.1	3.269	2.979
Inverse kinematic analysis time (s)	787.78	535.64	403.24
Number of experiments	5	5	5
Average working time (s)	87.35	60.08	37.12

- Simulation experiments show that the intelligent obstacle avoidance path planning method provided in the paper can reduce path length and the number of path nodes during obstacle avoiding, compared with the ordinary artificial potential field method in Section 3.

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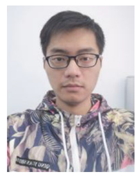

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