TRAJECTORY PLANNING FOR COLLABORATIVE OPERATION OF MULTIPLE AGRICULTURAL HANDLING ROBOTS BASED ON IMPROVED WHALE OPTIMIZATION ALGORITHM
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基于改进鲸鱼优化算法的多农业搬运机器人协同作业轨迹规划研究

Jiahao LAN, Yunjie MA *)
School of Economics and Management, Ningbo University of Technology, Ningbo, Ningbo/ China
Tel: +8619157501635; E-mail: flmyj123@163.com
Corresponding author: Ma Yunjie
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ABSTRACT
To solve the problem that the moving trajectory and operating trajectory are relatively independent and time-consuming when robots transfer agricultural products from harvesting fields to warehouses or transport vehicles, a type of agricultural materials handling robot was designed, the optimal trajectory planning method for the collaborative operating time of agricultural materials handling robots was proposed, and the time optimal trajectory under the collaborative operation of robot operating system and traveling system was acquired. Specifically, the kinematic model and dynamic model for the collaborative operation of robots were established to perform time optimal trajectory planning for materials handling robots, the Beta distribution was then applied to the Whale Optimization Algorithm (WOA) for population initialization, and a nonlinear convergence factor was introduced to prevent local optimum in the later stage of iterations. Finally, WOA was improved combining the variable neighborhood algorithm to enhance the diversity of the neighborhood structure, and this improved algorithm was applied to model solving. The results reveal that the proposed trajectory planning method can facilitate robots to obtain a smooth and time optical moving trajectory in collaborative operations of materials grabbing and discharging and obstacle avoidance. The displacement, speed, acceleration, and force/torque curves of each joint of the robots change gently, and the double-crawler traction can meet the requirements of the robots and rapidly stabilize and track the time optical trajectory.

摘要
为了解决机器人将农产品从收获场所转移到仓库或运输车辆存在的移动轨迹和作业轨迹相对独立且耗时长的问题，本文设计一种农业物料移运机器人，并提出一种农业物料移运机器人协同作业时间最优轨迹规划方法，获得机器人作业系统和行驶系统协同作业的时间最优轨迹。该方法建立机器人协同作业的运动学模型和动力学模型，对物料移运机器人开展时间最优轨迹规划，并将 Beta 分布应用于鲸鱼优化算法(Whale Optimization Algorithm，WOA)进行种群初始化，再引入非线性收敛因子改善迭代后期陷入局部最优的情况，最后结合变邻域算法改进了鲸鱼优化算法来增加邻域结构的多样性，并将此算法应用于该模型求解。结果表明，提出的轨迹规划方法可使机器人在抓放料协同作业和避障协同作业中取得平滑且时间最优的运动轨迹，机器人各关节的位移、速度、加速度、力/力矩曲线变化平缓，两履带牵引力满足机器人的要求且可快速稳定跟踪时间最优路径。

INTRODUCTION
As an important starting point to promote agricultural modernization, the development of agricultural robots is of great significance for improving agricultural production efficiency, popularizing new agricultural technologies, protecting farmland environment, and reducing dependence on human resources. Agricultural robots will contribute to agricultural automation, informatization and intelligence, thus changing the operation mode of traditional agriculture (*Wang et al., 2022*). Under the increasing pressure of environmental protection, agricultural robots, if applied, will also help protect the farmland environment and avoid the pollution of soil and groundwater caused by the excessive use of chemical fertilizers and pesticides (*Huo et al., 2018*). Nowadays agricultural robots can complete some heavy and trivial agricultural tasks, such as sowing, spraying, fertilizing, harvesting, and weeding so as to reduce the labor intensity of farmers and relieve their dependence on human resources. Meanwhile, handling robots, which have been widely used in such fields as industry, storage,

manufacturing, and service, are usually divided into fixed and mobile types (*Long et al., 2017*). Usually installed in production lines, machine tools, etc., agricultural handling robots can automatically perform assembly and handling tasks through programming, maintaining high working accuracy and efficiency (*Yin et al., 2023*). When facing the unknown environment, agricultural handling robots first collect environmental information through Lidar or depth cameras to build a map. Secondly, they can run autonomously in the workspace with obstacles through preset commands or real-time control of the upper computer; finally, the user can use the mouse, keyboard or program to complete the handling task (*Zhang et al., 2020*). Therefore, the collaborative system of multiple agricultural handling robots is an important development direction of robot application at present. Compared with the single agricultural robot system, the collaborative system of multiple agricultural robots can not only solve complex tasks and improve the robustness and reliability of the system but also has been successfully applied to logistics warehouse handling and agricultural handling. At present, however, most of these tasks are realized by manual teaching, lacking the ability of independent motion planning. As the requirement for intelligent production is put forward in China, the multi-agricultural-robot collaborative system should have the ability to plan the motion independently, making it very necessary to study the motion planning of the multi-agricultural-robot collaborative system.

Literature review

At present, many algorithms have been used in robot path planning. *Wang et al. (2019)* proposed a wireless positioning system based on ZigBee, which can locate the handling robot in real time and give instructions for cargo handling. *Chen et al. (2019)* came up with a method based on greedy algorithm to meet the needs of temporary route adjustment of handling robots. *Božek et al. (2016)* raised a method to identify and judge the medical garbage bin based on machine vision, and the robot Lidar can navigate to the target garbage bin when receiving the start signal. *Palleschi et al. (2020)* implemented a map construction method based on laser SLAM, which exhibits higher mapping accuracy and serves as the suitable map construction method for handling robot path planning. *Abu-Dakka et al. (2017)* proposed an improved artificial potential field method for path planning of handling robots, which solved the failure of traditional algorithms to reach the target point. *Daniel et al. (2019)* put forward an improved ant colony algorithm to plan the path of handling robots, which can elevate the speed of the handling robots and reduce the loss. Among many algorithms, A* algorithm is considered a common and appropriate algorithm to solve the path planning problem of handling robots by virtue of its rapid response to the environment and direct path search. In some literature, A* algorithm has been used to solve the path planning problem of robots. *Sathiya et al. (2019)* proposed an improved A* algorithm, which introduced a "reward and punishment mechanism" on the basis of single handling robot and obstacle prediction, thus reducing the number of turns of the handling robot in the moving process. *Amruta et al. (2020)* proposed a robot path planning method combining A* algorithm with dynamic window method, and improved the smoothness of the path. *Park et al. (2020)* proposed an improved A* algorithm, which improved the actual operation efficiency of robots, reduced their energy consumption, and shortened the time of path search planning. Although A* algorithm has been used to plan the motion path of handling robots so that they can avoid all obstacles and safely deliver the goods to the destination, the efficiency of A* algorithm will significantly decline if handling robots work under large environments, and the planned path is usually not the optimal one.

The research on path planning of robots mainly includes path generation and path tracking. First of all, path generation refers to the path with the shortest generation time or the least energy consumption, which is mainly solved by particle swarm optimization algorithm, ant colony algorithm, firefly algorithm, and genetic algorithm. *Seyedali et al. (2016)* could generate motion paths in complex areas by setting constraints and collision models and discretizing variables at equal intervals. *Elhosseini et al. (2019)* proposed a path generation algorithm based on obstacle cost potential field to dynamically adjust the path, contributing to the smooth motion path of robots and keeping them at a safe distance from obstacles. *Chen et al. (2019)* put forward a double-optimized ant colony algorithm to adaptively adjust the probability transfer function and re-optimize the path to solve the low convergence path quality in path planning. *Ahmed et al. (2019)* proposed an improved potential field ant colony algorithm, constructed a negative feedback channel through the convergence times of the algorithm, and dynamically adjusted the update speed of parameters to obtain the optimal path. *Gu et al. (2021)* used ant colony algorithm and geometric method to optimize the path, and combined pheromone diffusion with geometric local optimization to generate a global optimal path. Path tracking refers to controlling the robot to follow a specified path. For instance, *Li et al. (2020)* established the dynamic model of tracked vehicles based on the principle of spherical contact, and designed a tracking controller by using deep reinforcement learning, which can accurately track the path. *Tu et al. (2021)* came up with a path tracking method based on heuristic dynamic programming, which integrated the tracking error and tracking stability of the path to design a return function to enhance the environmental adaptability of path tracking. *Heidari et al. (2019)* raised a fuzzy predictive control algorithm combining the dynamics characteristics of the robot to track the path, so as to solve the high time delay in high-speed trajectory tracking control. *Li et al. (2021)* could generate a better path in the target space by combining various algorithms, but the calculated quantity was large, which degraded the efficiency and real-time performance of path generation to some extent; the tracking control law stated by *Hu et al. (2021)* is complex, and it is difficult to determine the optimal control law parameters. In face of the requirements for the efficient operation of agricultural robots, studying the coordination between robot operating system and traveling system is an important development opportunity and challenge for agricultural robots *(Hu et al., 2021)*. Some problems have been found in the existing research. For example, the research on path planning of robots needs to be determined in advance and the action completed by the collaborative operation of the traveling system and operating system is relatively simple, making it difficult to realize real-time trajectory planning under complex scenarios.

To sum up, the research on the handling path of robots mainly focuses on single-robot handling path planning, while the trajectory planning through the collaborative operation of multiple agricultural handling robots has been less investigated. Based on the abovementioned research results, a trajectory planning model for the collaborative operation of multiple agricultural handling robots was constructed in this study. Then, the population was initialized using Beta distribution based on the basic Whale Optimization Algorithm (WOA), a nonlinear convergence factor was added to prevent the algorithm from local optimum in the later stage of iterations, and the diversity of the neighborhood structure was enhanced by introducing the variable neighborhood algorithm. As revealed by the comparison results with basic WOA, the improved algorithm can effectively improve the model solving efficiency.

MATERIALS AND METHODS

Collaborative kinematics analysis of agricultural handling robots

When a rigid body is collaboratively handled by 2 agricultural handling robots, the base of each robot is fixed, and then the homogeneous transformation (BWT) from the base coordinate system {B} of each robot to the world coordinate system {W} is fixed. The two handling robots are set to jointly hold the workpiece and do linear motion with an unchanged pose, so the coordinate system {U} of the workpiece will change constantly. Taking the world coordinate system {W} as a reference, the initial pose and the target pose of the workpiece are expressed as Formulas (1) and (2) respectively:

$$ {}_{U}^{W}T^{start} = \begin{bmatrix} {}_{U}^{W}R & {}_{U}^{W}P^{start} \\ 0 & 1 \end{bmatrix} \tag{1} $$

$$ {}_{U}^{W}T^{goal} = \begin{bmatrix} {}_{U}^{W}R & {}_{U}^{W}P^{goal} \\ 0 & 1 \end{bmatrix} \tag{2} $$

Hence, the straight path is $L = \sqrt{(P^{start} - P^{goal})^2}$ in length, which is equally divided into N portions, and then N+1 path points are generated. Therefore, the N+1 pose sequence of {U} about {W} is displayed in Formula (3):

$$ \left\{ {}_{U}^{W}T(k) = \begin{pmatrix} {}_{U}^{W}R & P(k) \\ 0_{1\times 3} & 1 \end{pmatrix} \right\}, 0 \leqslant k \leqslant N \tag{3} $$

The motion at the ends of the two handling robots about the base coordinate system is respectively calculated as per Formulas (4) and (5):

$$ {}_{E_1}^{B_1}T(k) = \begin{pmatrix} W \\ B_1 \end{pmatrix} T^{-1} \begin{pmatrix} W \\ U \end{pmatrix} T(k) \begin{pmatrix} U \\ E_1 \end{pmatrix} \tag{4} $$

$$ {}_{E_2}^{B_2}T(k) = \begin{pmatrix} W \\ B_2 \end{pmatrix} T^{-1} \begin{pmatrix} W \\ U \end{pmatrix} T(k) \begin{pmatrix} U \\ E_2 \end{pmatrix} \tag{5} $$

Given the fixed values of WBT and UET, it is only necessary to solve the pose $({}^{W}_{U}T(k))$ of {U} relative to {W}, and then the motion at the ends of the two handling robots about their base coordinate system is solved. Furthermore, the change $\{{}^{1}q_n\}(1 \le n \le 6)$ in each joint of Robot 1 and that $(\{{}^{2}q_n\}(1 \le n \le 6))$ of Robot 2 can be solved through inverse solutions.

In this section, the changes in the joints of the 2 robots can be solved through the collaboration model of multiple agricultural handling robots established, thus laying a foundation for establishing the path optimization function subsequently.

Modeling

The path selection function for agricultural handling robots is established with their operating length fr_1, operating difficulty index fr_2, and operating time fr_3 as the objective functions. For the objective function fr_1, the available motion path of agricultural handling robots is assumed to be $R=\{r_1, r_2, \ldots, r_n\}$ and the number of nodes on the available motion path to be n. fr_1 is calculated through the following formula:

$$fr_1 = \sum_{i,j=1;i\neq j} d\left(r_i, r_j\right) \tag{6}$$

Where r_1, r_j represent the i-th and j-th nodes on the available path; $d(r_1, r_j)$ denotes the distance between r_1 and r_j.

The total difficulty index fr_2 of each node in the path passed by agricultural handling robots is calculated as follows:

$$fr_2 = \sum_{i=1}^{n} z_i g\left(r_i\right) \tag{7}$$

Where $g(r_i)$ is the difficulty index when the handling robot passes r_i; z_i denotes the number of robots passing any node within a designated time window.

The objective function fr_3 is calculated as below:

$$fr_3 = \sum_{i,j=1}^{n}\sum_{a=1}^{A} x_{ar_{ij}}\left(t_{ij}^{s}\cdot w_{ij} + t_{ij}^{c} + t_{\mathrm{w}}\right) \tag{8}$$

Where A is the number of agricultural handling robots; $x_{ar_{ij}}$ stands for the number of handling tasks; t_{ij}^{s} is the time needed by the agricultural handling robot to pass the straight road section from node i to j; t_{ij}^{c} represents the time needed to pass the turning road segment from node i to j; w_{ij} is the weight of the road segment from node i to j; t_{w} is the time window.

t_{ij}^{s} is calculated as follows:

$$\mathrm{t_{ij}^{s}} = \frac{\mathrm{L(i,j)}}{\mathrm{v_s}} - \frac{\mathrm{L_v}}{\mathrm{v_s}} \tag{9}$$

Where v_{s} represents the uniform running speed of agricultural handling robots; $L(i,j)$ is the distance between i and j; L_v is the length of agricultural handling robots.

$$t_{ij}^{\mathrm{c}} = \frac{L_{\mathrm{v}}}{v_{\mathrm{c}}} + \frac{\pi R_{\mathrm{tc}}}{v_{\mathrm{c}}} \tag{10}$$

Where v_{c} is the running speed of agricultural handling robots at the turning; R_{tc} represents the turning radius of robots.

In this study, three objective functions, operating length, operating difficulty index, and operating time, were designed when constructing the trajectory planning model of multiple agricultural handling robots, aiming to achieve the optimal trajectory for the collaborative operation of multiple agricultural handling robots. By assigning different weights to different optimization objectives, the objective functions were subjected to dimensionless processing uniformly through the following formula.

$$fr_1^{*} = \frac{fr_1 - \min fr_1}{\max fr_1 - \min fr_1} \tag{11}$$

$$fr_2^* = \frac{fr_2 - \min fr_2}{\max fr_2 - \min fr_2} \tag{12}$$

$$fr_3^* = \frac{fr_3 - \min fr_3}{\max fr_3 - \min fr_3} \tag{13}$$

The three objective functions of the unified dimension were weighted and summed according to the specified weights and transformed into a single-objective model for solving. The expression of the single-objective function is:

$$\min fr^* = \alpha_1 fr_1^* + \alpha_2 fr_2^* + \alpha_3 fr_3^* \tag{14}$$

Where α_i is the weight of the objective function and $\alpha_i \in [0,1]$, $\alpha_1 + \alpha_2 + \alpha_3 = 1$.

Constraints

The multiple constraints for the established motion path selection function of handling robots are expressed as follows:

$$x_{ar_{ij}} = 1 \tag{15}$$

$$t_w = t_{r_{ij}}^{a,\text{end}} - t_{r_{ij}}^{a,\text{start}} \tag{16}$$

$$\begin{cases} N_{r_{ij}}^{t_{r_{ij}}^a} = r_{ij} \cdot \sum_{a=1}^{A} x_a^{t_{r_{ij}}^a} \\ N_{r_{ji}}^{t_{r_{ji}}^a} = r_{ji} \cdot \sum_{a=1}^{A} x_a^{t_{r_{ji}}^a} \end{cases} \tag{17}$$

$$z_i \geqslant N_{r_{ij}}^{t_{r_{ij}}^a} + N_{r_{ji}}^{t_{r_{ji}}^a} \tag{18}$$

Formula (15) is the handling task constraint of handling robots, i.e., any handling robot can only execute one task in intelligent storage; Formula (16) is the time window constraint, namely, the time window t_w constraint of Robot a on path r_{ij}. Formula (17) constrains the number of handling robots within the time window, namely, it is the constraint for the number of handling robots within a designated time window; Formula (18) constrains the number of handling robots on the path within the designated time window, i.e., the constraint for the number of handling robots on r_{ij} within $t_{r_{ij}}^a$.

ALGORITHM DESIGN

How to solve the path optimization problem accurately and efficiently has always been a major problem. In the existing studies, heuristic algorithms have often been used to solve similar problems. As a type of heuristic algorithm, WOA has enjoyed extensive development and application because of simple mechanism, few parameters, and strong optimization ability. Model solving can be achieved more rapidly and effectively by improving the standard WOA.

WOA

WOA is a meta-heuristic optimization algorithm proposed in 2016, which is inspired by the hunting behavior of humpback whales. By simulating the hunting behavior of random or optimal individuals, researchers have found that there are two kinds of bubble net hunting methods for whales, i.e., "upward spiral strategy" and "double spiral strategy". In the "upward spiral strategy", the humpback whale will dive by about 12 m first, then start making bubbles in the spiral, and swim to the surface. The "double spiral strategy" includes three different links: coral link, whale tail flapping on the water surface link, and capture link. The above predation process can be applied to solving WOA, that is, one solution can be expressed by one whale individual, and multiple solutions can be expressed by multiple whale individuals. The idea of solving WOA can be equivalent to the fact that many whales are constantly changing their positions until searching a satisfactory solution.

(1) Prey encirclement

It is assumed that in a d-dimensional space, the position of the optimal whale individual X^* is $(X_1^*, X_2^*, ..., X_d^*)$, and the position of the whale individual X^j is $(X_1^j, X_2^j, ..., X_d^j)$. The next position X^{j+1}

$(X_1^{j+1}, X_2^{j+1},..., X_d^{j+1})$ of the whale individual X^j under the influence of the optimal whale individual is calculated as follows:

$$X_k^{j+1} = X_k^* - A_1 D_k \quad (19)$$
$$D_k = | C_1 X_k^* - X_k^j | \quad (20)$$
$$C_1 = 2r_2 \quad (21)$$
$$A_1 = 2ar_1 - a \quad (22)$$
$$a = 2 - 2t / t_{max} \quad (23)$$

Where X_k^{j+1} is the k-th component of the space coordinate X^{j+1}; the convergence factor a linearly declines from 2 to 0 with the increase in the number of iterations; t is the current number of iterations; both r_1 and r_2 are random numbers within [0,1].

(2) Prey capturing

When the whale individuals approach the current best whale individual in a spiral way to catch their prey, half of them will choose to shrink the ring of encirclement, while the other half will choose to run to the prey in a spiral way.

$$D_k = | X_k^* - X_k^j | \quad (24)$$

When p < 0.5,

$$X_k^{j+1} = X_k^* - A_1 D_k \quad (25)$$

When p≥0.5,

$$X_k^{j+1} = X_k^* + D_k \exp(bl) cos(2\pi l) \quad (26)$$

Where b is the logarithmic spiral shape constant and l is a random number within [-1, 1].

(3) Prey search

In the mathematical model for prey capturing behavior, the value of A_1 is restricted within [-1, 1]. If the value does not fall into this range, whale individuals will randomly select a whale individual to approach from the current whale individuals. It is assumed that the spatial position of a random whale individual X^s in the whale population is $(X_1^s, X_2^s,..., X_d^s)$, and then the mathematical model for prey search behavior is displayed as below:

$$X_k^{j+1} = X_k^s - A_1 D_k \quad (27)$$
$$D_k = | C_1 X_k^s - X_k^j | \quad (28)$$

Improved WOA

Generally, when the NPL problem is solved using swarm intelligence algorithms, the algorithm performance is mainly affected by premature convergence and convergence speed, and it is especially important to balance the exploration and development abilities of algorithms in search space (*Zhang et al., 2019*). Particle Swarm Optimization (PSO) has fast convergence speed but weak global exploration ability. WOA displays good exploration ability, but its development ability is mainly restricted by the distance between the current position and the optimal position. In PSO, if the global optimal solution of the population falls into a local optimum, other particles will stop searching and follow the global optimal solution into the local optimum. To sum up, the PSO algorithm has strong optimization ability but weak space exploration ability, and WOA is characterized by strong space exploration ability, but its optimization ability is restricted by the convergence speed. Therefore, PSO can be applied to the development stage of WOA to improve the ability of the algorithm to get the global optimal solution.

Hybrid PSO-AWOA is a combination of PSO algorithm and WOA. By introducing nonlinear weight factors into PSO algorithm and WOA, the shortcoming of PSO algorithm, namely, the restriction of a constant inertia weight, which results in a small scope of search space, is overcome. Meanwhile, in WOA, a nonlinear inertia weight is introduced to shrink the ring of encirclement and update the spiral migration position, which accelerates the algorithm convergence and enhances its optimization ability (Li et al., 2020). Hybrid PSO-AWOA absorbs the respective advantages of the two, thus showing more prominent optimization performance

(*Ding et al., 2021*). The inertia weight factor is the dominant factor balancing the global search ability and local development ability of the algorithm. In this study, the adaptive inertia weight strategy was adopted and the nonlinear weight w was introduced. As the number of iterations grew, the value of w changed dynamically. In the initial stage of iterations, a large weight could improve the global exploration ability of the algorithm. In the later stage, however, a small weight could facilitate the refined local optimization of the algorithm.

W is updated through the following formula:

$$w = \left[1 - \sin\left(\frac{\pi}{2} \times \frac{t}{\text{Max\_iter}}\right)\right]^k \tag{29}$$

Where: k is the adjustment coefficient, and the weight w changes with the k value. In addition, the change rate of weight w varies with the k value. PSO-AWOS expects a relatively large weight value in the initial stage of iterations so that the algorithm can possess strong global search ability and a high convergence speed. With the increase in the number of iterations, the weight declines sharply in the middle stage of iterations and approaches 0 slowly in the later stage, which improves the convergence speed and solving accuracy of the algorithm. Through repeated experiments, k=1.8 was taken in this study (*Huang et al., 2021*).

After the nonlinear weight is introduced into the hybrid algorithm, the position update formula of WOA algorithm is as follows:

$$X(t+1) = w \times X^*(t) - A \times D \tag{30}$$

$$X(t+1) = D' \times e^{bl} \times \cos(2\pi l) + w \times X^*(t) \tag{31}$$

$$X(t+1) = w \times X_{\text{rand}} - A \times D \tag{32}$$

The particle movement speed and position of the PSO algorithm are updated as per the following formula:

$$V_{id}(t+1) = w \times V_{id}(t) + c_1 r_1 \times \left[X^*(t) - X_{id}(t)\right] \tag{33}$$

$$X(t+1) = X_{id}(t) + V_{id}(t) \tag{34}$$

Steps of improved WOA

The specific implementation steps of improved WOA are described as below:

Step 1: population and algorithm parameter initialization. The position of the whale population and particle swarm is randomly initialized as $X_i = (X_{i1}, X_{i2}, \cdots, X_{id})$ and the movement speed as $V_i = (V_{i1}, V_{i2}, \cdots, V_{id})$, where $i = 1, 2, 3, \cdots, M$. Meanwhile, the population size M, the maximum number of iterations Max_pop, the dimension d of search space, and the initial number t of iterations should be initialized to calculate the fitness value of each individual in the population. Next, the position X_best of the optimal individual is found through comparisons:

Step 2: The values of coefficients A and C are updated as per Formulas (22) and (23), so are the values of b, l, c_1, and r_1, generating a random number p within [0,1];

Step 3: Position updating based on the values of p and $|A|$. If $p < 0.5$ and $|A| \geq 1$, the whale individual X_{rand} is randomly selected from the population, followed by position updating as per Formulas (17) and (30); if $p < 0.5$ and $|A| < 1$, position updating is then implemented according to Formulas (17) and (30); if $p \geq 0.5$, position updating is performed through Formula (31);

Step 4: The movement speed of individuals in the particle swarm is updated according to Formula (33), and the position X of the particle swarm is updated through Formula (34);

Step 5: Return to Step 2 for iterative updating and judge whether the maximum number of iterations is reached. If iterations of the algorithm are completed, the implementation of the algorithm is terminated;

Step 6: The algorithm iteration is completed. Return to the finally calculated optimal position X_best and solve the individual position of the population in case of the optimal value. Thereby, solving is completed.

RESULTS

To further verify the practicability and feasibility of the hybrid PSO-AWOA proposed in this study, the working environment of robots was simulated using the traditional grid map. Obstacles exist in the black region and the black region is a feasible region, where the starting point and endpoint of robots are (1,1) and (100,100), respectively; the boundary of the map is the outermost area of the whole path planning, which is regarded as an obstacle.

Hardware environment and parameter settings

The hardware platform of the experiment is Windows, the processor is Intel Core i5-14600K, the memory is 8 GB, and the software platform is Matlab2014b. The relevant parameter settings of each compared algorithm are listed in Table 1.

Table 1

Parameter settings of each algorithm

Algorithm	Parameter
WOA	b=1
PSO-AWOA	$b=1, c_1=2, w=1-\sin\left(\frac{\pi}{2}\times\frac{t}{Max\_iter}\right)^k, k=2.2$

Path planning simulation experiment

The experimental environment was a 100 m×100 m grid map, the agricultural handling robot moved from the starting point to the target point, and obstacles existed in the black region. In the simulation experiment, the same parameters were adopted for the 2 algorithms, for example, the initial population size was 50, the maximum number of iterations was 200, and the scope of search space was [-100,100] for both. To ensure the optimality of the generated path, the generation direction of the path was further defined in the path generation stage, that is, the path would not be "turned back" or "looped back", and the barrier-free region of the generated path point was simply optimized by interpolation or direct connection, thus ensuring the optimality of the path. Finally, the performance of the algorithm was assessed by statistically analyzing the length of the planned path, time consumption, and the number of inflection points generated by the algorithm. The planned path obtained through the simulation experiment is exhibited in Fig. 1. The length of the optimal path found by the PSO-AWOA algorithm under the 100 m ×100 m complex environment was 140.67 m, the algorithm converged at 1.77 s, and the optimal path was achieved after 114 iterations.

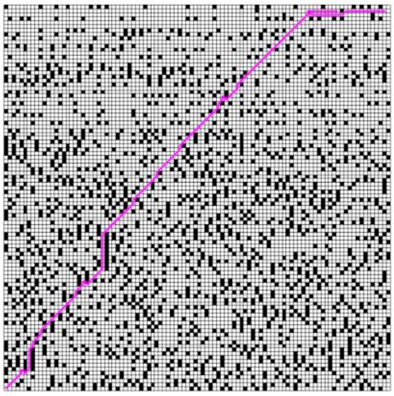

Fig. 1 - PSO-AWOA path planning

To verify the effectiveness of hybrid PSO-AWOA in solving the path planning problem of robots, standard WOS and hybrid PSO-AWOA established in this study were subjected to the comparative simulation experiment under a complex multi-obstacle simulation experimental environment. The handling path of agricultural robots obtained by standard WOA is displayed in Fig. 2. The length of the optimal path found by WOA under the 100 m×100 m complex environment was 179.94 m, the algorithm converged at 2.38 s, and the optimal path was harvested after 168 iterations.

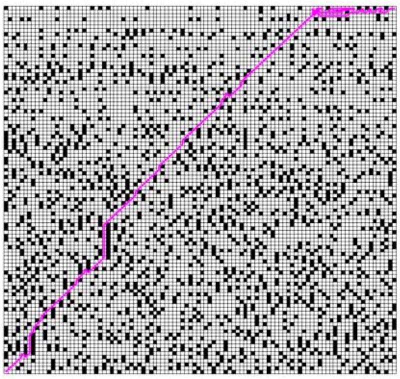

Fig. 2 - WOA path planning

Finally, the performance of the algorithm was evaluated by statistically analyzing the length of the planned path, time consumption, and the number of inflection points generated by the algorithm. The comparative data on the time consumption, number of iterations leading to convergence, the path length, and the number of inflection points on the path planned by PSO-AWOA and WOA are listed in Table 3.

Table 3

Experimental results of complex scene simulation

Algorithm	Time-consuming / s	Convergence algebras (algebras)	Path length / m	Number of inflection points (number)
PSO-AWOA	1.77s	114	140.67m	27
WOA	2.38s	168	179.94m	39

By comparing the time consumption, the number of iterations leading to convergence, the path length, and the number of inflection points on the path obtained by the two algorithms, it could be known that PSO-AWOA averagely spent 1.77 s, which was 0.61 s shorter than that of WOA, and the efficiency was improved by 34.46%. In the complex environment with many obstacles, PSO-AWOA algorithm acquired the optimal path after 114 iterations, and the length was 140.67 m; WOA achieved the optimal path after 168 iterations, and the length was 179.94 m; the number of inflection points on the path obtained by PSO-AWOA was 27 while that by WOA was 39, indicating that the robot path solved by PSO-AWOA was smoother. The above data and analysis manifest that PSO-AWOA can be successfully applied to the path planning problem of robots, and its convergence accuracy and convergence speed are both improved no matter under simple scenarios or complex scenarios.

CONCLUSIONS

In this study, the time optimal trajectory planning method for the collaborative operation of multiple agricultural handling robots was proposed to solve the relatively independent moving trajectory and great time consumption in the collaborative operation of multiple agricultural handling robots and the collaborative operation of obstacle avoidance. Then, three objective functions, operating length, operating difficulty, and operating time, were established and the multi-objective function was transformed into a single-objective function through the weighting method, aiming to achieve the optimal trajectory of multiple agricultural handling robots in collaborative operation. Moreover, an improved WOA based on PSO and adaptive inertia weight was proposed. Next, PSO with relatively strong optimization ability was introduced into the development stage of WOA to balance the exploration and development abilities of the algorithm. Meanwhile, adaptive weight factors were introduced so that the improved algorithm could possess a relatively large weight in the initial stage of iterations and fully explore the unknown space. In the later stage of iterations, the algorithm weight presented a nonlinear reduction, and the algorithm could realize refined search within a local scope. Finally, the improved algorithm was used to solve the path planning problem of robots in a grid map environment, verifying that the algorithm can solve the optimal collision-free motion path of multiple agricultural handling robots faster. In the follow-up study, the improvement room for the algorithm performance will be further explored in real environments and dynamic obstacle-containing environments.

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