GLOBAL PATH PLANNING OF FARMLAND PLOTS BASED ON IMPROVED WHALE OPTIMIZATION ALGORITHM
/
基于改进鲸鱼优化算法地块整体路径规划

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ABSTRACT
Path planning is crucial for agricultural machinery navigation. To address the issue of operational path planning in fields with obstacles, this paper proposes a method for obstacle avoidance path planning in farmland by combining an improved whale optimization algorithm with Dijkstra's algorithm. The population initialization is conducted using Tent mapping and a nonlinear convergence factor α^* is introduced to reduce the oscillation and instability of the traditional whale optimization algorithm. By using the grid method to model the environment of the target field, the field is divided into multiple regular subplots. The improved whale optimization algorithm is employed to determine the optimal traversal order of these subplots. Subsequently, Dijkstra's algorithm is applied to find the shortest path connecting the subplots, achieving global obstacle avoidance path planning for farmland. Taking a rectangular plot of land in Jiaolai Town, Jiaozhou City, Qingdao as the target area for this study, the experimental results indicate that this method achieves a coverage rate of 100% in the plot coverage path experiment. Additionally, the path redundancy rate is 4.87%, which represents a reduction of 1.63% compared to traditional algorithms. This research method is applicable to regular plots, but it still has limitations for irregular plots or those with curved boundaries.

摘要
路径规划是农机导航的关键。针对地块中存在障碍物的作业路径规划问题，本文旨在提出一种基于改进鲸鱼优化算法与Dijkstra 算法相结合的农田避障路径规划的方法。本文通过利用Tent 映射进行种群初始化，以及引入非线性收敛因子α^*，降低传统鲸鱼优化算法的振荡性以及不稳定性。通过栅格法对目标地块进行环境建模，将地块分成多个规则子地块,通过改进鲸鱼算法求解子地块最佳遍历顺序，再利用 Dijkstra 算法进行子地块之间连接最短路径，实现农田全局避障路径规划。以青岛市胶州市胶莱镇的一块矩形地块为本次研究目标地块，实验结果表明：本方法在目标地块覆盖路径实验中，地块覆盖率达到 100%，路径重复率为 4.87%，路径重复率较传统算法减少 1.63%。该研究方法适用于规则地块，对于不规则或边界为曲线的地块还存在局限性。

INTRODUCTION
Path planning is one of the key technologies for achieving autonomous navigation operations in agricultural machinery (*Deng H et al., 2023*). The rationality and efficiency of path planning directly impact the accuracy and quality of agricultural machinery operations. The presence of structured obstacles in fields, such as utility poles, buildings, and irrigation devices, poses a significant challenge in avoiding these obstacles and achieving comprehensive coverage in path planning for agricultural machinery navigation. For the problem of full coverage path planning in agricultural fields, there are currently two main approaches: local path planning and global path planning methods. Local path planning refers to the process of obtaining real-time information about obstacles surrounding the working path through perception sensors in situations where the field environment is unknown, with an emphasis on the safety and timeliness of the path (*Chakraborty, S et al, 2022*). Global path planning refers to the process of planning a global path when the environmental information of the field is known, aiming to achieve full coverage of the target area.

Currently, there is limited research on path planning for agricultural machinery both domestically and internationally. Regarding local path planning*, Wang Zhen, (2023),* utilized an improved ant - colony algorithm with embedded genetic operators to solve for the optimal path of virtual nodes. Taking the transportation cost and time cost of agricultural robots as the objective function, the effectiveness of the optimization model and the improved ant - colony algorithm was verified through case analysis. *Li Fan, (2023),* classified obstacles based on the relationship between the size of field obstacles and the working width of agricultural machinery. They proposed a method for obstacle avoidance using polyline techniques to bypass small obstacles by segmenting and merging the field. In 2023, someone proposed a method for constructing the shortest tangent obstacle avoidance path, which can quickly plan an obstacle avoidance path in the case of static obstacles *(Huo Yinghui et al., 2023).* For global path planning, *Nilsson et al., (2020),* represented the coverage trajectory of farmland as a virtual road network diagram consisting of main working area trajectories, headland passages, and turning trajectories. Finally, coverage path planning was conducted based on this diagram. Experimental results demonstrate that this method is applicable to various types of single fields; however, it is not suitable for fields with obstacles*. Yakoubi et al., (2016),* addressed the problem of complete coverage for cleaning robots using a genetic algorithm. They iteratively optimized the path length as the fitness function and employed genetic operators such as crossover and mutation to enhance fitness. This algorithm achieved complete coverage in simple environments; however, its drawbacks include low search efficiency in the later stages and poor convergence*.* Le proposed an algorithm for complete coverage path planning based on a spiral generation tree, utilizing genetic algorithms (GA) and ant colony optimization to solve the Traveling Salesman Problem (TSP). However, a notable drawback of this approach is the occurrence of dead zones in areas with a high density of obstacles. Additionally, the resulting path length and the number of turns are relatively unsatisfactory *(Le et al., 2020).*

In summary, regarding the path planning problem in plots with obstacles, both local path planning and full coverage paths have certain deficiencies. For example, existing local path planning methods often adopt the shortest tangent method and polyline method, where the obstacle avoidance strategies are overly simplistic, considering only a single obstacle, and lack universality in situations where multiple obstacles are present in the plot. The research on global path planning faces issues such as low algorithm efficiency, poor convergence performance, and an inability to handle areas with multiple obstacles. To address the above issues, this paper proposes a path planning method for obstacle-laden plots based on an improved whale optimization algorithm. Firstly, the target plot is modeled using a grid method. Then, the plot is segmented and merged based on the obstacles present, dividing it into multiple sub-plots that are free of obstacles. An intelligent algorithm is used to determine the traversal order of the sub-plots, while Dijkstra's algorithm is employed for path planning between the sub-plots. This ultimately achieves full coverage path planning for the entire plot.

MATERIAL AND METHODS

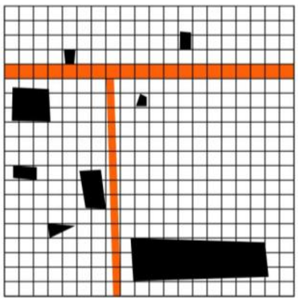
Construction of Operational Model

Grid Modeling of the Plot

In this study, a grid modeling method is utilized to create a representation of the target plot. This method defines the grid size based on key parameters such as the length, area, and obstacle information of the target plot, using the operational range of smart agricultural machinery as a reference. The entire environment is then divided into several square cells, referred to as grids, where each grid represents a specific area within the environment. These grids effectively capture obstacle information and clearly illustrate features of free space and other environmental characteristics, thereby simplifying the complex environmental data into a manageable set of two-dimensional grid representations *(Deng et al., 2023).*

The target plot is a farmland located in Jiaolai Town, Jiaozhou City, Qingdao, Shandong Province, with coordinates at 36.43°N latitude and 120.05°E longitude. The digital elevation model (DEM) data indicates that the plot has a total area of 130,040 square meters and a perimeter of 1.443 kilometers. The contour feature points of the field and the obstacles within the farmland have been marked (as shown in Figure 1). In this paper, based on the information of the target plot and the working range of the agricultural robot, a 20×20 grid model is constructed in MATLAB R2023a. The white grids represent the workable grids, the black grids represent the obstacle grids. A grid that contains obstacles but is not completely filled is defined as a partial - obstacle grid; a grid that is completely filled with obstacles is called a full - obstacle grid (as shown in Fig. 3).

Real - scene satellite image



Plot raster modeling

Fig. 1 – Overall structure of the cleaning device

Expansion of Obstacle Grids

Considering the varying shapes and sizes of obstacles in the field, some obstacles cannot fully occupy an entire grid cell, which increases the difficulty of algorithmic planning. Obstacles can also lead to path planning becoming trapped in local optima. Therefore, it is necessary to expand certain obstacles. When irregular obstacles do not occupy a full grid cell, their boundaries should be extended outward until the obstacles completely fill the grid cell they are in, thereby reducing the planning complexity. The specific rules for expanding obstacles are illustrated by the variations presented in Figure 2. According to these rules, the grid map in Figure 3 undergoes obstacle expansion, with the results shown in Figure 3.

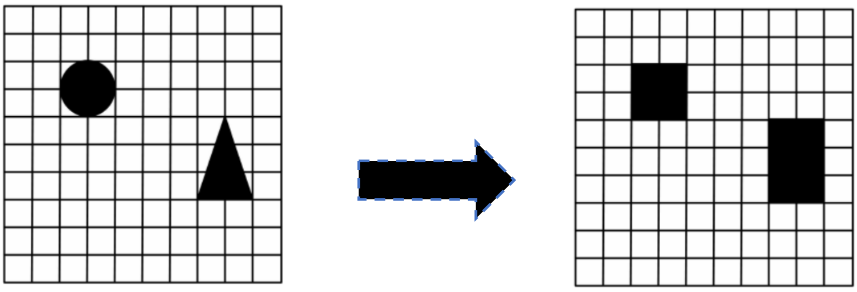


Fig. 2 – Obstacle Expansion Before and After

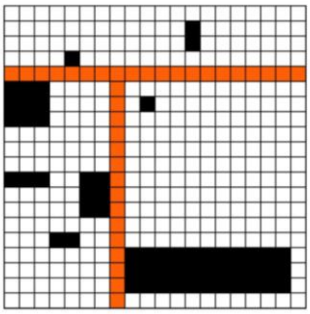


Fig. 3 – Obstacle Expansion Grid Map

Plot Division and Merging

This paper addresses obstacle avoidance path planning in farmland by partitioning the plots. The area decomposition method is employed to achieve this segmentation *(Tang et al., 2021).* Due to the presence of obstacles, the farmland is divided into multiple subplots, which can lead to an increased frequency of turns and lower coverage rates during agricultural operations. By utilizing the unit decomposition method, the farmland plots are segmented into multiple obstacle-free subplots *(Wang L. et al., 2024).*

The division of plots should be based on the grid map expanded above the obstacles. For each obstacle grid, parallel boundary lines to the X-axis and Y-axis are drawn from the two vertices at the bottom of the obstacle grid. These boundary lines extend outward until they encounter the next obstacle grid, and by repeating this process, the entire grid map can be segmented into multiple regular subplots. To reduce the operational redundancy and improve efficiency, adjacent subplots that have the same height or width should be merged to maximize the rectangular plots, thereby decreasing the number of subplots. The results of the plot division and merging are shown in Figure 4.

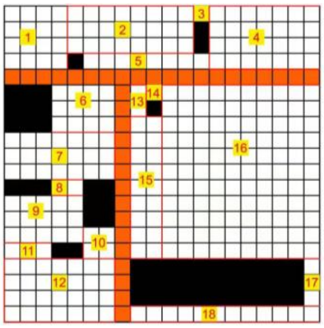


Fig. 4 – The results of the sub-plot division diagram

Sub-plot Traversal Order Planning

To achieve path planning for agricultural robots and reduce the rate of traversal duplication, it is essential to ensure that each defined sub-plot is planned exactly once in the global traversal path. This can be transformed into solving the Traveling Salesman Problem (TSP). The shortest path solution to the TSP corresponds to the optimal traversal order of the defined sub-plots. This study employs an improved whale optimization algorithm to determine the optimal traversal order among the sub-plots.

Traditional whale optimization algorithms

The whale optimization algorithm is a novel bio-inspired swarm intelligence algorithm, inspired by the foraging strategies of humpback whales *(Nadimi-Shahraki et al., 2023).* Within the framework of the whale optimization algorithm, each whale represents a feasible solution, and position updates are performed through encircling prey, bubble-net attacking, and random search.

(1) Encircling prey

In the encircling prey phase, it is assumed that the current best candidate is the target prey or an optimal solution close to the target prey *(Wei F. et al., 2023).* Once the best candidate solution is determined, all other whales will swim towards the direction of the best candidate solution, updating their positions in the process. The mathematical model for this process is as follows:

$$X(t+1) = X_{best}(t) - A \cdot D \tag{1}$$

$$D = |C \cdot X_{best}(t) - X(t)| \tag{2}$$

In the formula, t represents the current iteration number; $X_{best}(t)$ denotes the position vector of the current best candidate solution, and $X(t)$ is the position vector of the current whale. The coefficients A and C are vector coefficients, which are calculated as follows:

$$\mathrm{A} = 2\mathrm{ar} - \mathrm{a} = \mathrm{a}(2\mathrm{r} - 1) \tag{3}$$

$$C = 2\mathrm{r} \tag{4}$$

$$a = 2 - \frac{2t}{T} = 2(1 - \frac{t}{T}) \tag{5}$$

In the formula, a is the convergence coefficient; r is a random vector within the range of [0, 1], and T is the maximum number of iterations.

(2) Bubble Net Attack

Bubble net feeding is a unique predation behavior of humpback whales, which can be simulated using the following two mathematical models.

Constricting encirclement mechanism

The bubble net feeding technique is a unique foraging behavior of humpback whales used to capture prey, which can be simulated using the following two mathematical models.

Spiral position update

During this stage, the whales swim upstream in a spiral pattern, releasing bubble nets of varying sizes to capture prey. The mathematical model for this process is as follows:

$$\mathrm{X(t+1)} = \mathrm{D_{best}} \times \mathrm{e^{bL}} \times \cos(2\pi\mathrm{L}) + \mathrm{X_{best}(t)} \tag{6}$$

$$D_{best} = |X_{best}(t) - X(t)| \tag{7}$$

In this equation, D_{best} represents the distance between the current search individual and the current optimal solution; b is the spiral shape parameter; and L is a random number uniformly distributed in the range of [-1, 1].

Assuming that humpback whales have an equal probability of adopting these two behaviors when attacking prey, this can be expressed using the following formula (8).

$$X(t+1) = \begin{cases} X_{best}(t) - A, & p < 0.5 \\ D \cdot e^{bL} \cdot \cos(2\pi L) + X_{best}(t), & p \geq 0.5 \end{cases} \tag{8}$$

In the equation, P represents the probability of the predation mechanism, which is a random number within the range of [0, 1].

(3) Searching for prey

To ensure that all humpback whales can thoroughly explore the solution space, they conduct random searches based on their relative positions (*Yan Z. et al, 2023*). When |A| ≥ 1, the whales perform a global search, and the mathematical model is as follows:

$$D_{rand} = |C * X_{rand}(t) - X(t)| \tag{9}$$

$$X(t+1) = X_{rand}(t) - A \cdot D \tag{10}$$

In this formula, D_{rand} represents the distance between the current search agent and a random agent, while X_{rand} denotes the position of the random agent at the current time.

Improve the whale optimization algorithm

Compared with traditional optimization algorithms and early meta-heuristic algorithms, the whale optimization algorithm has its main advantages in strong local search capability, a simple structure, and fewer required tuning parameters *(Yang W. et al., 2023).* However, the traditional whale optimization algorithm also faces issues such as getting easily trapped in local optima and premature convergence. Considering the advantages and disadvantages of the whale optimization algorithm, this paper aims to improve the initialization phase and the convergence factor.

(1) Improve the initialization phase

During the initialization phase, the quality of the whale population directly influences the performance of the algorithm. However, the whale optimization algorithm employs a random and uncertain strategy to generate the initial population, which fails to ensure the diversity of the population. This lack of diversity in the initial population negatively impacts the overall effectiveness of the algorithm. This paper proposes to incorporate Tent mapping into the initialization phase of the whale optimization algorithm. Tent mapping is characterized by its regularity, randomness, and strong traversability, making it an effective solution to the quality issues of the initial population in the traditional whale optimization algorithm. The Tent mapping formula is as follows:

$$X(t+1) = \{\mu \cdot X(t), \quad 0 < X(t) < 0.5 \tag{11}$$

Assuming the initial whale population size is M, the population is represented as $X = \{X(t), 1, 2, 3, 4, \ldots\ldots\ldots.., M\}$. where $\mu \epsilon (0,2)$ is the chaos parameter, and the chaotic effect is directly proportional to its value—the larger the value, the better the chaotic effect. When $\mu = 2$ the population exhibits good ergodicity and algorithmic solving speed, allowing for a more comprehensive search of a larger space within a certain range. This enables the selection of outstanding individuals from the current population as initial solutions, thereby improving the quality of the population and the performance of the algorithm.

(2) Incorporate the nonlinear convergence factor

To address the issues of the whale optimization algorithm easily falling into local optima and premature convergence, an analysis of the operational logic of three search mechanisms reveals that the efficiency of global and local search in the algorithm is determined by the magnitude of the vector coefficient $||A|$ *(Chen X. et al., 2020)*. In the whale optimization algorithm, the convergence factor α exhibits a linearly decreasing trend. Therefore, when the number of iterations exceeds half of the maximum iteration count, $\alpha < 1$. In the iterative process, if the vector coefficient decreases prematurely to a low value, it increases the likelihood of the algorithm falling into a local optimum. To better balance the global search and local search capabilities of the algorithm, this study introduces a nonlinear convergence factor α^*, as shown in the following formula:

$$\alpha^* = 2 - \frac{2}{e^{-0.2(t-T/2)}} \tag{12}$$

Let the maximum number of iterations be $T = 80$. The convergence factor curve is illustrated in the figure below. In the iteration data graph, during the early and mid-stages of the iteration process, the value of α^* remains at a high level to ensure the global search ability of the algorithm. In the later stages of the iteration, α^* rapidly decreases to ensure that the algorithm focuses on local search. The improved workflow of the Whale Optimization Algorithm is illustrated in Figure 6.

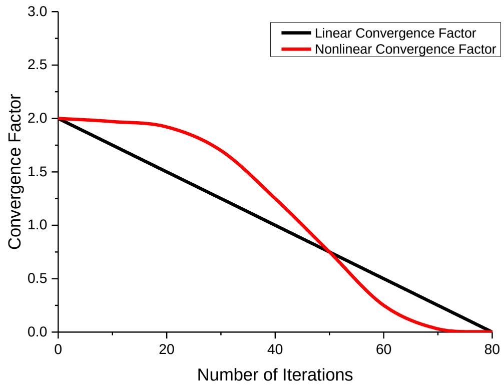


Fig. 5 – Convergence Factor Curve Graph

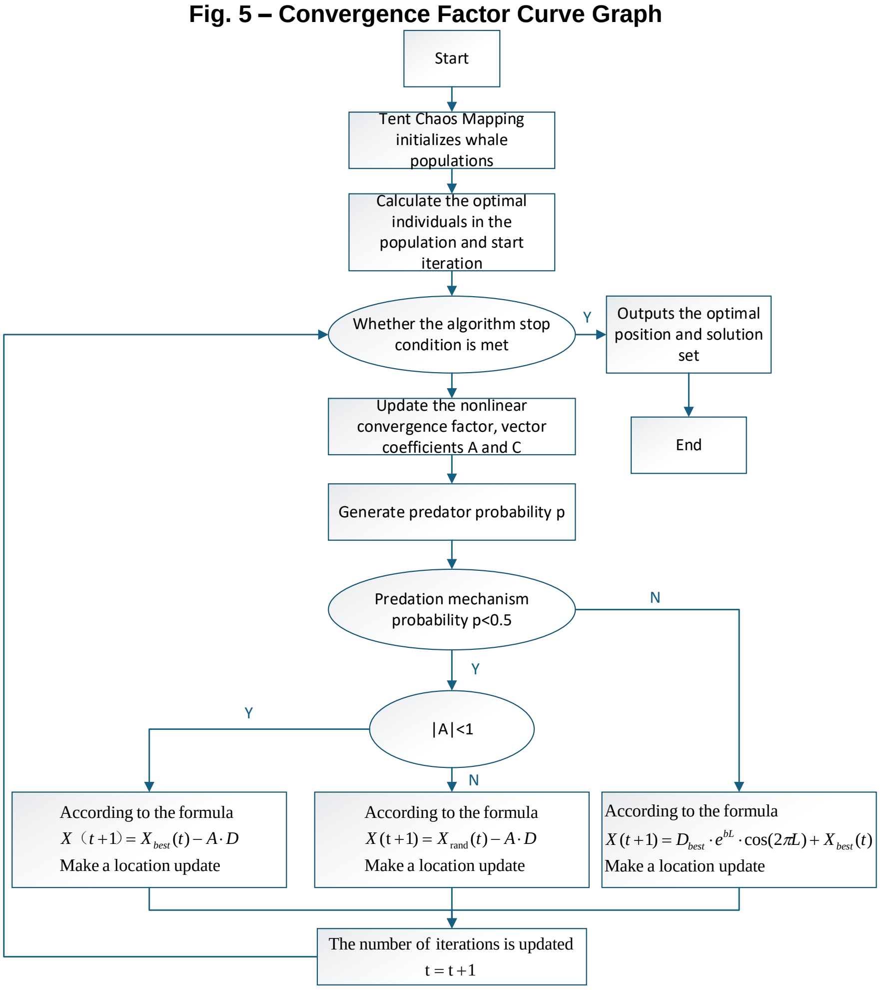
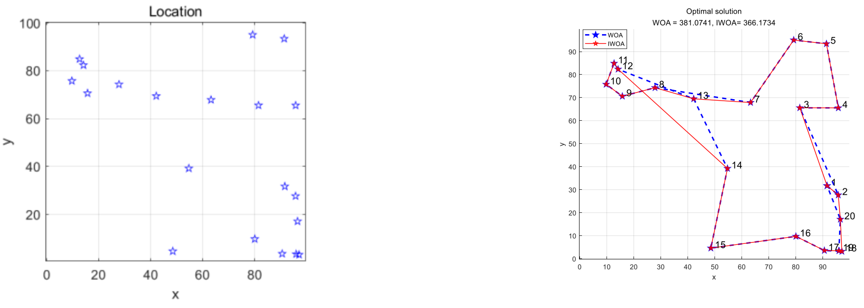


Fig. 6 – Algorithm Technical Roadmap

Improved simulation experiment of whale optimization algorithm

To demonstrate the superiority and advanced nature of the improved Whale Optimization Algorithm in solving the Traveling Salesman Problem (TSP), a comparative experimental method is employed. Both the traditional Whale Optimization Algorithm and the improved Whale Optimization Algorithm are utilized simultaneously to solve the TSP. This allows for a direct comparison of their performance and effectiveness in finding optimal or near-optimal solutions. Randomly generate coordinates for 20 cities and use the path length as the fitness value.

Figure 7a) shows the randomly generated coordinates of 20 cities, while Figure 7b) presents a comparison of the optimal traversal paths obtained using the improved whale optimization algorithm and the traditional whale optimization algorithm. This simulation was carried out in MATLAB R2023a on a Lenovo Legion Y7000 device.



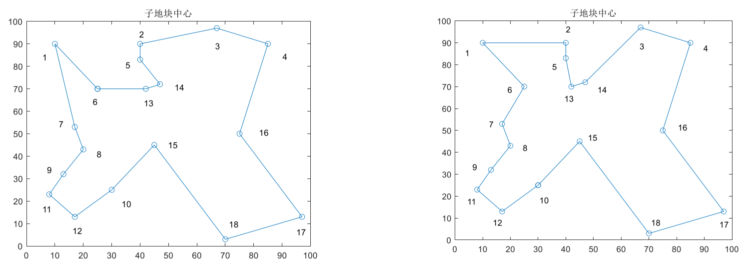
a) Location *b) Traversal Path Comparison*

Fig. 7 –Results of WOA and IWOA in Solving the TSP Problem

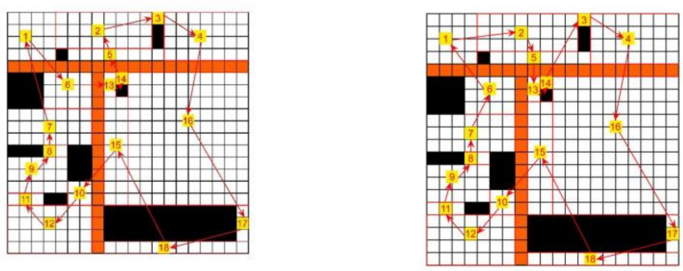
From Figure 7, it can be observed that the best fitness values for the Whale Optimization Algorithm (WOA) and the Improved Whale Optimization Algorithm (IWOA) are 381.0741 and 366.1734, respectively, indicating a reduction in fitness of approximately 3.9%. Based on the simulation results, it is evident that the solution obtained using the improved whale optimization algorithm for solving the Traveling Salesman Problem (TSP) with respect to the traversal order is significantly better than the results obtained using the traditional whale optimization algorithm.

Determine the optimal traversal order of the target sub-block

After validating the superiority of the improved whale optimization algorithm in addressing the traveling salesman problem, it is necessary to apply the improved whale optimization algorithm to the path planning for complete coverage of target plots. Based on the results of subplot division shown in Figure 4, for the convenience of planning the traversal order of regular subplots, the center coordinates of regular subplots will represent each subplot, and coordinate parameters will be used to indicate the specific locations of the subplots. Input the coordinates of the central points for each subplot; determine the optimal traversal order among the 18 subplots. The optimal traversal order between the target subplots is determined using both the traditional whale optimization algorithm and the improved whale optimization algorithm. The results are shown in the figure 8.



Traversal Order Solved by Whale Optimization Algorithm *Improved Whale Optimization Algorithm for Solving Traversal Order*



Schematic Diagram of Subplot Traversal Order in Whale Optimization Algorithm *Schematic Diagram of Improved Subplot Traversal Order in Whale Optimization Algorithm*

Fig. 8 –Comparison of traversal order results of subplots

Table 1

Comparison of traversal results from different algorithms

The name of the algorithm	Traversal order	Fitness value
WOA	6-13-14-5-2-3-4-16-17-18-15-10-12-11-9-8-7-1-6	403
IWOA	16-17-18-15-10-12-11-9-8-7-6-1-2-5-13-14-3-4-16	401

According to the observations from Figure 8 and Table 1, the optimal traversal order obtained by the traditional whale optimization algorithm for the subplots is: 6-13-14-5-2-3-4-16-17-18-15-10-12-11-9-8-7-1-6, with a shortest distance of 403 meters. In contrast, the optimal traversal sequence derived from the improved whale optimization algorithm is: 16-17-18-15-10-12-11-9-8-7-6-1-2-5-13-14-3-4-16, resulting in a shortest distance of 401 meters.

Path Planning within Agricultural Subplots

Based on the grid layouts and the presence of obstacles, the plots are divided into multiple regular subplots that are free of obstacles. While irregular subplot structures are simpler, effective path planning for the regular subplots requires selecting appropriate agricultural machinery operating methods to achieve optimal results. Currently, the primary coverage methods for operations in regular plots include reciprocating and inward spiral traversal techniques, as shown in Figure 9. The objective of path planning is to enhance operational efficiency, reduce cost waste, and minimize issues such as re-tilling and missed tilling.

The inward spiral traversal method for path planning typically involves frequent turns, making it inconvenient to connect with adjacent subplots. This can lead to increased energy consumption and reduced operational efficiency. Therefore, this study opts for the reciprocating method for path planning of the subplots to enhance land utilization and reduce occurrences of re-tilling and missed tilling. The specific steps for reciprocating traversal are as follows: (1) Choose a starting point and set the coordinates of the starting point as (x_0, y_0); (2) Define the two edges of the rectangular plot as A and B; (3) Determine the lengths of edges A and B, using the longer edge as the starting edge, with edge A aligned along the X-axis and edge B along the Y-axis. (4) If edge A is longer, the coordinates of the next point will be $(x_0 + 1, y_0)$. (5) If edge B is longer, the coordinates of the next point will be $(x_0, y_0 + 1)$.

Reciprocating *Inward spiral traversal techniques*

Fig. 9 – Coverage-Based Path Planning Method for Regular Plots

Subplot Connectivity Path Planning

After dividing the land into multiple subplots, agricultural robots complete traversal tasks within a single subplot area. They need to move from the current rectangular subplot to the next subplot based on the sequence of all subplots. In the path planning for connecting these two subplots, this study employs Dijkstra's algorithm for shortest path planning to reduce the redundancy of traversal paths and improve overall efficiency. The specific operational steps for using Dijkstra's algorithm for shortest path planning between points are as follows: First, read the data, set the source point a and the target point b, then mark the source point a and set $da = 0$, with $pb = 0$; Subsequently, examine the distances between all marked points k and unmarked points h, and update $d_k = [d_k, d_k + m_{kh}]$. Here, m_{kh} represents the distance between points k and h. Select the unmarked point i with the smallest d_h, then find the point h^* among the marked points that is directly connected to i, and set $i = h^*$, followed by marking i. Continue this process in a loop until all points are marked. The algorithm can accurately generate the optimal path between two points, specifically achieving the shortest path from the starting point to the target point for agricultural robots.

RESULTS

Simulation of Path Planning for the Entire Agricultural Plot

All the experiments presented in this paper were conducted on a dedicated server operating under the Windows 11 system. The server is powered by an Intel(R) Core(TM) i5 - 9300H CPU, featuring a base clock frequency of 2.40 GHz and paired with 16 GB of RAM. For graphics processing, an NVIDIA GeForce RTX 4060 graphics card with 6 GB of video memory was employed. The programming and simulation tasks were accomplished using MATLAB R2023a as the development language.

In the previous sections, the traversal order between the target plot and its subplots has been determined using both the traditional whale optimization algorithm and the improved whale optimization algorithm. The starting point is determined within the initial plot, and a reciprocating planning approach is employed for the subplots of the initial plot. Subsequently, the next working area is accessed from the current regular subplot. The shortest path planning is performed using the aforementioned Dijkstra algorithm, facilitating the determination of the shortest, collision-free walking path from the traversal endpoint of the previous regular plot to the traversal starting point of the next regular plot. This process is repeated in a loop, ultimately achieving a complete coverage path planning for the entire farmland plot. The final results are compared as shown in the figure10.

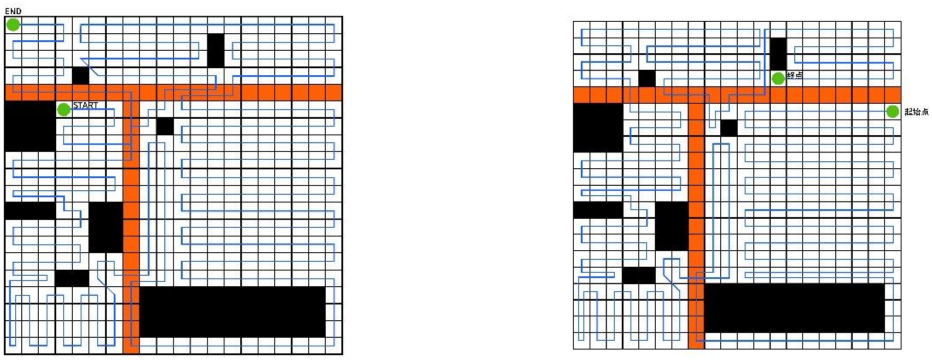


Diagram of Traditional Whale Optimization Algorithm for Path Planning *Diagram of Improved Whale Optimization Algorithm for Path Planning*

Fig. 10 – Path Planning Comparison Diagram

Table 2

Comparison Diagram of Path Planning

Path Planning Methods	Number of Covered Grids	Number of Duplicate Grids
Traditional Whale Optimization Algorithm and Dijkstra Algorithm	308	20
Improved Whale Optimization Algorithm and Dijkstra Algorithm	308	15

According to the observations from Figure 10 and Table 2, the entire grid consists of 20×20 cells, where black obstacles occupy 57 cells and roads occupy 35 cells, resulting in 308 free cells. The comparison shows that both algorithms achieve a coverage rate of 100%. Among them, the traditional whale optimization algorithm traverses 20 repeated cells, resulting in a traversal path redundancy rate of 6.5% and a path length of 4920 m. In contrast, the improved whale optimization algorithm traverses 15 repeated cells, achieving a traversal path redundancy rate of 4.87% and a path length of 4845 m. With the same coverage rate, the improved whale optimization algorithm reduces the path redundancy rate by 1.63% compared to the traditional algorithm. The experimental results indicate that the proposed method can effectively reduce path length, thereby validating the effectiveness of the research approach presented in this paper.

CONCLUSIONS

(1) This study proposes a stepwise path planning method for the entire agricultural plot area, which integrates an improved whale optimization algorithm with Dijkstra's algorithm. The method first employs the improved whale optimization algorithm to plan the traversal order of the segmented subplots, in order to determine the optimal traversal sequence for the subplots.

(2) To address the issues of local optimum entrapment and premature convergence commonly associated with the traditional whale optimization algorithm, this study utilizes Tent mapping for population initialization and introduces a nonlinear convergence factor. This approach balances the algorithm's global and local search capabilities, effectively mitigating local optima and significantly reducing search time. Experimental results using MATLAB indicate that, with 18 subplots, the improved whale optimization algorithm achieves a 4.07% reduction in average shortest path length and a 74.28% reduction in average iteration count compared to the traditional whale optimization algorithm.

(3) Using the path planning algorithm proposed in this study for full coverage of the target plots, MATLAB experiments reveal that the coverage rate of the paths generated by the improved whale optimization algorithm is 100%, with a repetition rate of 4.87%. This represents a reduction of 1.63% in repetition rate compared to the traditional whale optimization algorithm, thereby validating the effectiveness of the proposed method.

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