FIELD TRAVERSAL PATH PLANNING FOR AGRICULTURAL ROBOTS IN HILLY AREAS BASED ON DISCRETE ARTIFICIAL BEE COLONY ALGORITHM
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基于离散人工蜂群算法的农业机器人丘陵地区农田遍历路径规划

Xiaodong LOU [1], Zheng LI *[2]
[1] College of Digital Commerce, Zhejiang Business Technology Institute, Ningbo, Zhejiang/ China
[2] School of Teacher Education, Shaoxing University, Shaoxing, Zhejiang/ China
Tel: +8615968035670; E-mail: lizheng@nbu.edu.cn
Corresponding author: Zheng Li
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ABSTRACT
In this study, the discrete artificial bee colony (DABC) algorithm was proposed to plan the path of agricultural robots traversing multiple fields in hilly areas. Based on the basic ABC algorithm as the framework, the path coding method was adopted, and the discrete crossover operator, reverse operator, immune operator, and single/multi-step 2-opt operator were comprehensively used to help hired bees, observing bees, and scout bees to generate new food sources. Finally, the optimized field traversal order and the entrance and exit distribution of each field were obtained. The simulation results showed that compared with the traditional ABC algorithm, the average shortest path of the DABC algorithm proposed in this study was shortened by 1.59%, accompanied by the less iterations contributing to algorithm convergence and good ability to jump out of the local optimal solution. The simulation experiment was carried out using real field data and field operation parameters. The field traversal order and the entrance and exit distribution obtained by the proposed method can effectively reduce the length of the transfer path and its repeatability. This study exhibits superiority and feasibility in the field traversal path planning of agricultural robots in hilly areas, and the trajectory coordinates output by the algorithm can provide a path reference for large-area operations of agricultural machinery drivers or unmanned agricultural machineries.

摘要
本研究针对丘陵地区的农田环境下农业机器人遍历多个田块的遍历路径问题，提出了离散人工蜂群算法对农业机器人丘陵地区农田遍历路径进行规划。以基本人工蜂群算法为框架，采用路径编码的方式，综合运用离散交叉算子，逆转算子，免疫算子和单/多步 2-opt 算子以帮助雇佣蜂，观察蜂和侦察蜂产生新食物源，最终得到优化后的田块遍历顺序以及每个田块的进出口分布。仿真结果表明，与传统人工蜂群算法相比，本研究提出的离散人工蜂群算法平均最短路径缩短 1.59%，算法收敛迭代次数更少，并表现出较好的跳出局部最优解的能力。利用真实的农田数据和田间作业参数进行仿真试验，通过本研究方法得到的田块遍历顺序和进出口的排布能够有效地减少转移路径的长度和路径的重复率。本研究在农业机器人丘陵地区农田遍历路径规划上的优越性和可行性，算法输出的轨迹坐标能为农机驾驶员或无人农机在大面积作业时提供路径参考。

INTRODUCTION
Intelligent agricultural robots are an emerging technology in the field of agriculture, which is gradually being promoted and applied globally. The development of this technology began with the high automation and intelligence requirements of agricultural production. Agricultural technology enterprises from various countries have invested in research and development, and have achieved a series of research results. Intelligent agricultural robots have been widely used in fields such as traversing farmland, monitoring pests and diseases, and fertilizing herbs. It is based on high-precision sensors and advanced image recognition technology, which can autonomously inspect, identify pests and diseases, monitor meteorological data, and achieve big data analysis and decision support through cloud computing. In the field of farmland traversal, intelligent agricultural robots adopt advanced autonomous navigation and path planning algorithms, which can independently complete farmland traversal tasks and accurately cover the entire farmland. Compared to traditional manual traversal methods, robots have a faster traversal speed and can greatly improve the efficiency of agricultural production.

In China, the cultivated area in hilly and mountainous counties accounts for about 34.62% of national cultivated area, and the sown area accounts for 34.20% of the total sown area across China. The agricultural development in such areas is of crucial importance to the supply of agricultural products and facilitating farmers to get rid of poverty and become better off *(Xu et al., 2021)*. However, the field structure in hilly areas is obviously different from that in flat areas. Hilly areas are characterized by small irregularly and densely distributed fields with obstruction by ridges, which brings about a series of challenges to the operation of agricultural machineries and seriously impedes the mechanized and intelligent agricultural development *(Lan et al., 2021)*. Therefore, the development of intelligent agricultural machinery and equipment suitable for hilly areas is an important way to improve working capacity and quality, reduce costs, ensure national food security, and alleviate the shortage of rural labor *(Liu et al., 2020)*. In recent years, with the rapid development of mobile robot technology, intelligent equipment has been widely used in various fields of society, bringing great convenience to people's production and life. As a kind of agricultural robot, mowing robots are not only used for lawn mowing in municipal green spaces, airports, and golf courses but also for weeding in cultivated land and woodland, so they have drawn extensive concerns, and traversal path planning plays a vital role in the application of mowing robots *(Chen et al., 2022)*. Full-coverage traversal path planning is a special type of path planning in two-dimensional environment, which refers to finding a continuous path from the starting point to the end point and passing through all reachable points in a set area on the premise of satisfying some optimal performance indicators *(Zhang et al., 2017*). Up to now, a lot of research results have emerged regarding this technology. Intelligent agricultural robots have enormous development potential and broad application prospects in field traversal. Through efficient traversal ability, precise recognition function, diversified data collection, and intelligent operation interface, intelligent agricultural robots provide comprehensive technical support for agricultural production. With the continuous progress and promotion of technology, it is believed that intelligent agricultural robots will play an increasingly important role in the field of agricultural traversal, further promoting the modernization and intelligence of agricultural production (*Jeddisaravi et al.*, *2016*). In this study, therefore, a discrete artificial bee colony (DABC) traversal algorithm was proposed, which determined the traversal order of sub-areas after the target area was divided, and carried out cross-area transfer path planning to realize the field traversal path planning of agricultural robots in hilly areas.

Literature review

After the 1970s, industrial robots flourished and began to back-feed agriculture, and the most advanced technology in industrial robots was applied to the agricultural field, which resulted in a variety of agricultural robots with varied functions. Advanced technology was put into agricultural production, which significantly improved the efficiency of agricultural production (*Guruji et al.*, *2016*).

Rokbani et al., (2018), designed a double-heuristic ant colony optimization algorithm to solve the traveling salesman problem, which provided a theoretical basis for robot field traversal path optimization. To finish pesticide spraying and insect repellent tasks more accurately and efficiently, *Sun et al. (2017),* proposed an improved algorithm to solve the path optimization problem of mobile robots. *Zhao et al. (2018),* put forward the application of smooth AR (Augmented Reality) algorithm in intelligent vehicle path planning. *Zhao et al. (2018)* developed an autonomous robot that combined a novel obstacle separation algorithm and could continuously pick strawberries in multiple tunnels, making it possible for robots to pick strawberries located in the cluster. The obstacle separation algorithm pushes off the surrounding leaves, strawberries, and other obstacles through the gripper (*Zhao et al., 2018*). *Zeng et al. (2016)* developed a green agricultural robot based on machine vision technology. When conducting experiments on a field farm planed with pineapples, bananas, and apples, the robot collects the surrounding environmental information through cameras, sensors, and other equipment, feeds back the information to the monitoring personnel in real time, and walks freely among crops by using machine vision navigation technology. *Ding et al. (2021)* put forward an algorithm combining fuzzy logic with artificial potential field. When the robot falls into the local minimum, the fuzzy controller will generate an angle to change the current driving direction so that the robot can escape from local minimum and avoid obstacles safely *(Ding et al., 2021). Gu et al. (2021)* developed a new hybrid algorithm, that is, combining PSO with artificial potential field, which is applicable to complex scenarios with multiple obstacles. This algorithm can find the drivable path quickly, with short calculation time and high planning efficiency *(Gu et al., 2021).*

Wang et al. (2019) proposed an improved APF (Artificial Potential Field Method Path Planning Algorithm) method based on the dynamic window method to solve the tendency of robots to fall into the local minimum before reaching the destination. The points around the robot were evaluated in the local minimum through an evaluation function, and the best point was selected as the next path point *(Wang et al., 2019).*

Path planning, a key component of intelligent agricultural systems, can optimize the driving route of agricultural machinery and minimize repetitive work and time waste *(Li et al., 2020)*. Through reasonable path planning, agricultural machineries can cover fields efficiently, ensure that crops are fully cultivated and managed, and improve the crop yield and quality *(Wang et al., 2018)*. In agricultural production, the path covering field and generated by coverage path planning is used for agricultural machinery to perform specific operations, including harvesting, sowing, and fertilizing. The coverage path planning for a single field is mainly divided into two parts. First, a set of parallel straight-line trajectories are generated according to field data and agricultural machinery parameters. Secondly, parallel trajectories are connected to form an optimal trajectory sequence connected by arcs *(Tu et al., 2018). Heidari et al. (2019)* expressed the field coverage trajectory as the main operation area trajectory, the edge passage and the turning trajectory to construct a virtual road network map, and finally planned the coverage path based on the map. It is experimentally proved that this method is universal for all types of fields *(Heidari et al., 2019). Li et al. (2021)* adopted the simulated annealing algorithm to obtain the optimal path set, and solved the full-coverage traversal order through unit disassembly and synthesis. Compared with the traditional rule traversal method, *Li et al. (2021),* effectively dealt with different boundary constraints and greatly reduced the consumption of operations. Considering many warehouses for agricultural machinery replenishment around the field, *Song et al. (2019)* designed the connection paths for connecting warehouses, edge passages, and coverage paths, and used the simulated annealing algorithm to solve the traversal order between coverage paths. The existing research on multiple fields focuses on decomposing large-scale fields with complex shapes into several sub-fields with simple shapes according to certain laws, and then using intelligent algorithms to realize the optimal traversal sorting of sub-fields based on related traversal indexes. *Hu et al. (2021)* proposed a traversal algorithm combining memory simulated annealing with A* algorithm, which is a heuristic search algorithm widely used for path finding and graph traversal. First, the walking order of the optimal target point of the task was searched by memory simulated annealing algorithm, and then the cross-area connection path planning was carried out by A* algorithm. Considering the slope of fields in hilly areas, *Zhang et al.* (*2019*). obtained the optimal driving angle based on the energy consumption model of agricultural machinery, and then used genetic algorithm to obtain the optimal traversal order of multiple fields. The results show that this method can minimize the energy consumption of agricultural machinery to the greatest extent. To sum up, most of the existing studies are aimed at the coverage path planning of a single large field, while in a few studies on the traversal path planning of multiple fields, the linear distance is generally taken as the distance cost. Since the fields in hilly areas are small and densely distributed with obstruction by ridges, there lacks definite connected relations between fields, leading to the failure to form a continuous driving route between them and making it necessary to repeatedly seek for the appropriate position for transfer, which increases the operating time and costs. Given the aforesaid problems, this study aims to discuss the traversal route planning method of agricultural robots applicable to hilly areas. Through field investigation and data collection, the fields in hilly areas were surveyed in detail, and a method establishing the connecting related relations between fields was designed. Meanwhile, the DABC (Improved artificial bee colony algorithm based on differential mutation operator) traversal algorithm was put forward. Based on the road network diagram between fields, this distance was regarded as the distance cost required for inter-field transfer, and the optimal traversal order of multiple fields was obtained by DABC algorithm, thus realizing the multi-field traversal path planning of agricultural robots. This study aims to provide theoretical guidance and technical support for agricultural robots to realize continuous large-scale operations in hilly areas, so as to improve operation efficiency and agricultural production level.

MATERIAL AND METHODS

Search node positioning of intelligent agricultural network equipment

In this study, environment modeling of fields in hilly areas was performed using structural space method. The principle of structural space method is to express the working environment of robot through space modeling. At the same time, the structure space is integrated with the obstacle information and the pose information of the robot during operation. Then, the path search algorithm is used to solve a better safe path.

Voronoi diagram is a typical representative of structural space method. When constructing the model, Voronoi diagram regards the obstacle vertices in the environment as a set composed of multiple points. The trajectory formed by the points with close distance in the set is the edge of the map, and the vertex of the map is formed by the intersection of these trajectories. At the same time, these points are not allowed to penetrate the obstacle directly. This modeling method maximizes the distance between the obstacle and the robot. Therefore, it is difficult to find a better safe path when using this method to build an environment model.

The geometric characteristics of the agricultural robot traversing the environment were mapped into the geometric space for description through points, lines, and planes. In the actual traversal, it is necessary to reserve turning space and edge area according to the parameters of agricultural robots and traversal parameters. Hence, the field was divided into two functional areas: edge area and main traversal area. The edge area was used to meet the needs of agricultural robots to turn around and change lines. The main traversal area consisted of a series of parallel straight-line trajectories, in which agricultural robots carried out farming, sowing and other operations.

The calculation method of the edge area width W_h is shown in Formula (1).

$$W_h = r + \frac{\omega}{2} + r \times | cos\varphi | \tag{1}$$

where r represents the minimum turning radius of the agricultural robot; ω represents the traversal width; φ indicates the included angle between the traversal direction and the field boundary. According to this calculation method, the edge area and main traversal area of fields were constructed. The edge of the field, which is close to the field boundary, is specially used for agricultural robots to turn. When turning in the field, the agricultural robot will not make a specific traversal. This means that the agricultural robot can move in the edge area after completing the coverage traversal of the field in the main traversal area so that it can smoothly transfer to the next field. Such an arrangement can ensure that the agricultural robot can move between fields more efficiently and smoothly.

Fitness function

The following constraints need to be met in the process of agricultural robot's traversal path planning: the traversal path of the agricultural robot must be limited in the map space and cannot exceed the map boundary; the traversal path length of the robot is the shortest to ensure that the acquired path is the optimal one; the traversal path of the agricultural robot cannot cross the obstacle area of fields to avoid collision; because agricultural robots traverse terraces in hilly areas with a height difference in the traversal path, it is necessary to consider the influence of height change on the fitness function; according to the above constraints, the traversal path planning problem of agricultural robots can be abstracted as a single-objective optimization problem with the minimum fitness, and the fitness function of the problem can be derived as follows:

$$\min f = \sum_{i=1}^{n} L_{\text{path}}(i) + G_{\text{obstacle}}(p_i) \tag{2}$$

Among them: i is the number of algorithm iterations; $L_{\text{path}}(i)$ represents the length of the path planned for the robot upon the i-th iteration, which is specifically defined as below:

Where (x_i, y_i, z_i) stands for the position coordinates of the robot upon the i-th iteration; $(x_{i-1}, y_{i-1}, z_{i-1})$ denotes the position coordinates of the robot upon the i-1-th iteration; the solved $L_{\text{path}}(i)$ is the Euclidean distance between two points.

$$L_{\text{path}}(i) = \sqrt{(x_i - x_{i-1})^2 + (y_i - y_{i-1})^2 + (z_i - z_{i-1})^2} \tag{3}$$

$G_{\text{obstacle}}(p_i)$ is used to judge whether the path point p_i transcends the boundary or its ligature with the previous path point crosses the obstacle upon the i-th iteration. When the path point is feasible, the return value is 0, or otherwise, a relatively large constant $N \times N$ will be returned, which is specifically defined as follows:

$$G_{\text{obstacle}}(p_i) = \begin{cases} N \times N, p_i \ \text{ infeasible} \\ 0, p_i \ \text{ feasible} \end{cases} \tag{4}$$

Algorithm design

The DABC algorithm proposed in this study to solve the field traversal problem of agricultural robots in hilly areas included 5 main components, namely, control parameter initialization, bee colony (food source) initialization, hired bee stage, observing bee stage, and scout bee stage.

Control parameter initialization

The DABC algorithm has 3 control parameters, namely colony_Size, abandonment condition $limit$ and termination condition max_Evaluations. In the DABC algorithm, the whole bee colony contains an equal number of hired bees and observing bees, and each hired bee corresponds to a food source (that is, a solution in the solution space). Therefore, the number of food sources food_Number is half the size of the bee colony, that is, food_Number=colony_Size/2. For each food source S_i, the variable $trial_i$ records the number of times for which the food source has continuously not been improved during the search. If the corresponding $trial$ value of a food source exceeds the predetermined $limit$, the food source will be abandoned by the corresponding hired bees and replaced by a new food source randomly searched by the scout bees. The algorithm continuously repeats the hired bee stage, observing bee stage, and scout bee stage until the number of evaluations of the objective function (1) exceeds the allowed maximum value max_Evaluations, and then the algorithm terminates. Before the start of the DABC algorithm, the values of the above three control parameters need to be determined manually, and the algorithm performance is affected by different values of the control parameters (*Li et al., 2020*).

Bee colony initialization

As for bee colony initialization, the DABC algorithm encodes the food source in the order of field traversal. For n fields, each food source is encoded as a complete array from 0 to n-1. This encoding method has the following advantages: The legal constraints for field traversal of agricultural robots in hilly areas are hidden in bee colony initialization, crossover operation, and other operations, i.e., field number will not appear repeatedly. In the initialization stage, the algorithm, randomly generates food_Number food sources (solutions) according to the search space of the problem. Next, the objective function of random solutions is calculated so as to find the optimal (minimum objective function) food source gbest_Solution in the current bee colony is found. In this case, the number of evaluations is food_Number, and the trial of each food source is initialized as 0.

Hired bee stage

In the hired bee stage, for food source S_i, its neighbor is determined first. Here, "Neighbor" is defined as another food source randomly selected by the bee colony (*Han et al., 2019*). Then, one offspring individual of S_i and neighbor is generated using a crossover operator and evaluated after being applied with a reverse operator, an immune operator, and a single-step 2-opt operator. If Off_spring is better than S_i, S_i is replaced by Off_spring and $trial_i$ is set to 0, or otherwise, the value of $trial_i$ will increase by 1. If Off_spring is also better than gbest, gbest will then be updated.

Crossover operator: In this study, a partial matching crossover operator (PMX) was adopted. Specifically, one segment is randomly chosen from the two parent strings. A series of exchanges are defined using the elements of the two parent strings in the selected segment, which can execute respectively in each parent string to generate offspring chromosomes. For parent strings p1= ［6 5 1 ,7 4 0 2,3 8 9］ and p2= ［5 0 6, 3 8 1 7,2 9 4］, the sub-strings generated by the exchanges, which are defined by the elements in the selected segment, are q1= ［5 2 6,7 4 0 1,3 8 9］ and q2= ［5 0 6,3 8 4 7,2 9 1］, respectively.

Reverse operator: the traversal points between two different random positions in the path string are numbered in reverse order. This operator is beneficial to the small-scale migration of the algorithm.

Immune operator: Immune operator is a common technical means of solving the field traversal problem of agricultural robots in hilly areas. Specifically, a position pos is randomly chosen from the path string, and the nearest field is found around the traversal points corresponding to this position and inserted after pos. For example, p= ［6 5 1 ,7 4 0 2,3 8 9］, if the field number corresponding to the randomly selected position is 6 and the field number closest to field 6 is 2, then the new individual p'= ［6 5 2 ,7 4 0 1,3 8 9］ is obtained after the immune operator is executed.

Single-step 2-opt operator: Similar to the reverse operator, this operator numbers the traversal points between two different random positions in the path string in reverse order. Differently, before reverse ordering, it is necessary to judge whether the objective function is improved after reverse ordering. If yes, the reverse ordering will be implemented; if not, the original path string will keep unchanged *(Ding et al., 2021).* The 2-opt operator is a very effective local search technology for solving the TSP problem, which has been widely used in all kinds of evolutionary algorithms. The pseudo-code for the hiring phase looks like this:

For i=1 to foodNumber

1. For each solution S_i, determine its "neighbor"; // Use the crossover operator to generate offspring of S_i and its neighbors

2.Offspring =crossoverOperator(S,neighbor)// Perform the reversal operator on the Offspring

3.Offspring =inverseOperator(Offspring)// Immunizes the Offspring

4.Offspring =immuneOperator(Offspring)// Run the one-step 2-opt operator on the Offspring

5.Offspring =2-opt(Offspring)
6. Assess the Offspring
7.evaluations =evaluations +1
8. If (Offspring is better than S_i*) Replace* S_i *with Offspring*
trial[i]=0
else
trial[i]=trial[i]+1
9. Replace If(Offspring is better than gbestSolution) with Offspring
gbestSolution

Observing bee stage

In this stage, the observing bees will select individuals by means of roulette for improvement according to the food source information provided by the hired bees. The probability for the *i*-th food source to be chosen is denoted as $prob_i$, which is calculated as follows:

1) Calculate the objective function T_i of the *i*-th food source;

2) Find the minimum value min in all T_i;

3) Calculate $D_i = T_i - min$, $i = 1, 2, \ldots, FN$, in which *FN* denotes food_Number, i.e., the number of food sources;

4) Calculate $sum = \sum_{i=1}^{FN} D_i$;

5) If $sum > 0$, $prob_i = 1 - (0.9 \times \frac{D_i}{sum} + 0.1)$; if $sum = 0$, $prob_i = 1 / FN$.

In a specific bee colony, the minimum value min of the objective function for all food sources is fixed. If $sum > 0$ (namely, the objective functions of different food sources are not completely equal), $prob_i$ is calculated. In this case, the smaller the objective functions of food sources (the better), the smaller the D_i value, the greater the $prob_i$ value, i.e., outstanding food sources will be chosen at a relatively large probability. If $sum = 0$ (namely, the objective functions of all food sources are equal), the probability for each food source to be chosen is $prob_i = 1 / FN$.

After one food source is successfully selected, the observing bees will perform reverse and immune operations for this food source, followed by the execution of the multi-step 2-opt operator. For *n* traversal points, the 2-opt operation is implemented totally $n(n-1)/2$ times *(Huang et al., 2021)*, specifically as follows. The pseudo-code for the watch-bee phase looks like this:

Calculate the selection probability prob
i=0; t=0;
While t < foodNumber
If rand < prob[i]
1.t++; Offspring =S// Perform the reversal operator on Offspring
2.Offspring =nverseOperator(Offspring)// Immunize the Offspring
3. Offspring =immuneOperator(Offspring)// Perform the multi-step 2-opt operator on the Offspring
4.Offspring =exhausted2-opt(Offspring)
5. Assess the Offspring
6.evaluations = evaluations +1
7.I(Offspring is better than Si. Replace Si with Offspring
trial[i] = 0
else
trial[i] = trial[i] + 1
8.If(Offspring is better than gbestSolution)
Replace gbestSolution with Offspring
End If
i=i+1
If(i== foodNumber) i= 0
End While

Scout bee stage

The process of the scout bee stage is as aforesaid. When the trial value of one food sources exceeds the limit, the food source will be abandoned, and the corresponding hired bees will be converted into scout bees. First, the food source with the maximum trial value in the bee colony is found, and whether its trial value is greater than the limit is judged. If yes, a new food source (solution) is randomly generated and improved using the greedy strategy, followed by the implementation of the reverse, immune, and multi-step 2-opt operators. Finally, the new solution is evaluated and used to replace the original food source. In this stage, the greedy strategy is defined as follows: the first traversal point of the old solution is kept unchanged, and the traversal point nearest to the first one is found from the rest ones as the second traversal point, i.e., the traversal point nearest to the previous one is found each time as the next traversal point until all traversal points are traversed. The operation of the other operators resembles that in the hired bee and observing bee stages, which, therefore, will not be repeated hereby. The pseudo-code for the scout bee phase looks like this:

// Determine the food source with the maximum trial value
maxTrialIndex = 0
For(j=l; j<foodNumber; j++)
If (trial[j] > trial[maxTrialIndex])
maxTrialIndex =j;
End For
If trialmaxTrialIndex] > limit
1. Randomly generate a new food source solution
2. Adopt greedy strategy to improve solution// Implement reversal operator on solution
3.solution= inverseOperator(solution)// Applies the immune operator to the solution
4. solution= immuneOperator(solution)// Perform the multi-step 2-opt operator on the solution
5.solution= exhausted2-opt(solution)
6. Evaluate the solution
7.evaluations =evaluations +1
8. Replace the maxTrialIndex food source with solution
9.trial[maxTrialIndex] =0
End If

Example analysis

Simulation experiment

To verify the effect of the multi-field traversal path planning method proposed in this study, the simulation experiment was carried out using real field data and field operation parameters in MATLAB2014a programming environment. The actual operation area was chosen as the simulation object, with its satellite images displayed in Fig.1

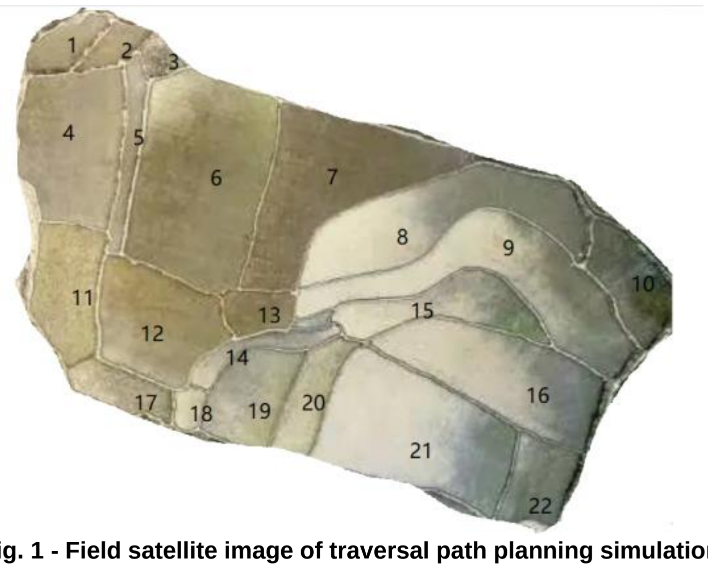

Fig. 1 - Field satellite image of traversal path planning simulation test

The working area consisted of 22 groups of fields, the boundary contour of which was irregular. The data parameters of each field are shown in Table 1. The working parameters of the agricultural robots were as follows: the minimum turning radius was 1.5 m, and the working width was 2 m.

In Fig.1, it is assumed that a vertical line at the leftmost endpoint is the Y axis of the coordinate system, and a horizontal line at the bottom endpoint is the x axis of the coordinate system, and the intersection of the x and Y axes is the origin of the coordinates.

Table 1

Traversal path planning simulation test field data parameters

Farmland serial number	Area (m^2)	Circumference (m)	coordinates (X) m	coordinates (Y) m
1	105	48	10.61	43.7
2	99	45	22.8	44.12
3	52	30	29.76	43.78
4	237	71	23.29	38.38
5	110	56	24.63	40.31
6	313	105	34.29	39.08
7	232	169	55.07	33.67
8	241	190	73.94	32.43
9	243	209	76.39	30.01
10	98	52	86.35	32.43
11	89	50	11.4	25.5
12	225	83	35.45	20.57
13	97	32	47.78	27.26
14	93	106	44.7	22.75
15	201	142	79.31	26.76
16	237	162	79.08	27.29
17	87	56	32.11	18.44
18	49	30	40.37	19.26
19	94	54	45.00	24.63
20	102	45	51.11	26.19
21	320	121	80.14	20.07
22	90	48	88.78	18.98

In this section, the DABC algorithm was mainly used to solve some test problems in the field traversal of agricultural robots in hilly areas, and the simulation results were recorded and analyzed. According to the parameter selection experiment in the previous section, the control parameters of the DABC algorithm were set as colony_Size=100, limit=500, and max_Evaluations=1,000,000. The number of independent operations was set toNt and the number of times to successfully find the theoretical optimal value to Ns, and then the success rate was Ns/Nt×100%. Agricultural robots must stop at all monitoring points in the process of traversing fields in hilly areas. The DABC algorithm and traditional ABC algorithm were respectively subjected to simulation tests, and the corresponding calculation results were compared.

RESULTS

To eliminate the influence of various random factors and verify the advantages and disadvantages of the DABC algorithm designed in this study, the DABC algorithm was used to optimize the traversal detection path of agricultural robots for 200 times. The convergence curve of the DABC algorithm is shown in Fig. 2. The optimal path of agricultural robot inspection is shown in Fig. 3

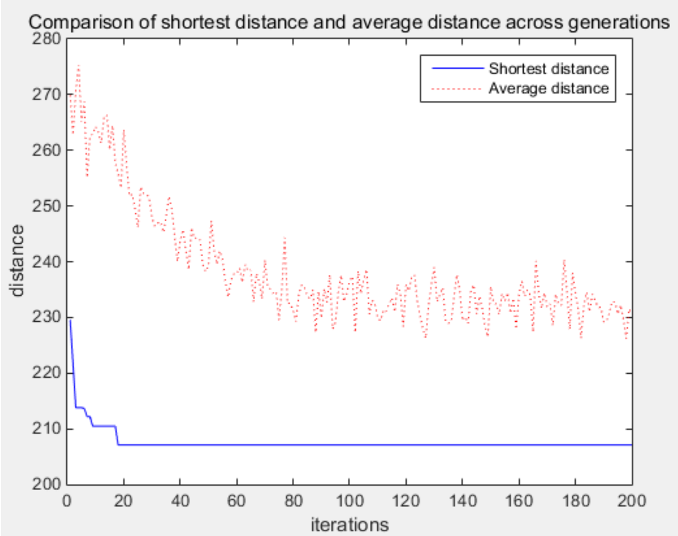

Fig. 2 - Convergence curve of discrete artificial bee colony algorithm

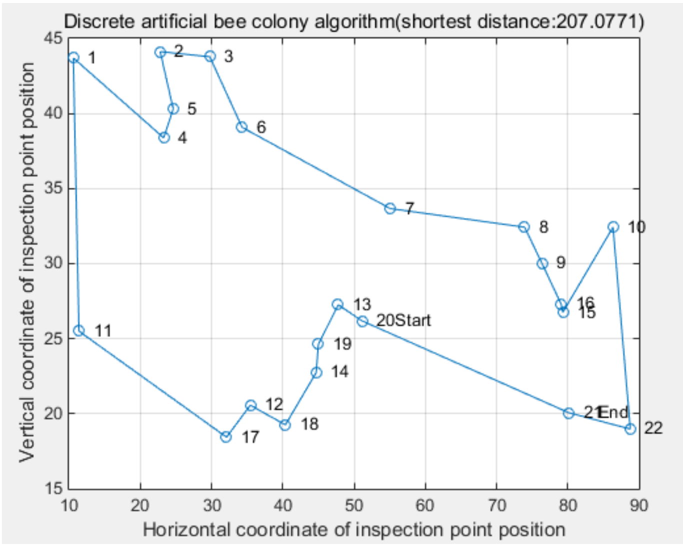

Fig. 3 - Agricultural robot traverses the optimal path(m)

To verify the effectiveness of the model and algorithm, the traditional ABC algorithm was used on the same platform, and the optimization model proposed in this study was solved with the same parameters. For the sake of more scientific and effective experimental results, the maximum number of iterations of the traditional ABC algorithm was also set to 200, and its convergence curve is exhibited in Fig. 4 and the optimal path traversed by agricultural robots is displayed in Fig. 5.

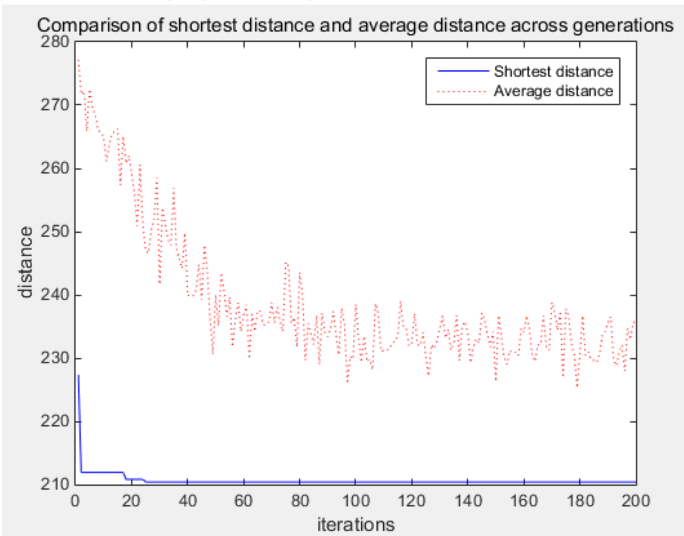

Fig. 4- Convergence curve of traditional artificial bee colony algorithm

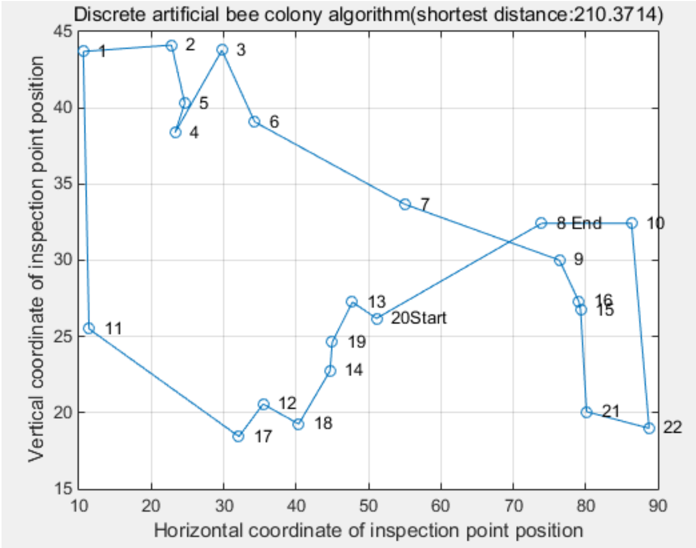

Fig. 5 - Agricultural robot traverses the optimal path

The DABC algorithm was compared with the traditional ABC algorithm in the inspection path, the total traversal travel distance of agricultural robots, and convergence time, as seen in Table 2.

Table 2

Comparison of discrete artificial bee colony algorithm and traditional artificial bee colony algorithm

Algorithm	Inspection path	Distance (m)	Algorithm convergence time (s)
Discrete artificial bee colony algorithm	20→13→19→14→18→12→17→11 →1→4→5→2→3→6→7→8→9→16→15 →10→22→21→20	207.08	56.17
Traditional artificial bee colony algorithm	20→13→19→14→18→12→17→11 →1→2→5→4→3→ 6→7→9→16→15→21→22→10→8→20	210.37	68.11

As seen in Table 2, the optimization ability and convergence of the DABC algorithm were stronger than those of the traditional ABC algorithm. It could be intuitively seen from the convergence curves of algorithms that in terms of the total traversal distance of agricultural robots, the optimal path length acquired by the DABC algorithm was better than that obtained through the traditional ABC algorithm. The total traversal distance of the DABC algorithm was 3.29 m shorter than that of the traditional ABC algorithm with a reduction of 1.59%; in the aspect of convergence time, the convergence time of the traditional ABC algorithm was longer than that of the DABC algorithm. In addition, the convergence time of the DABC algorithm was 11.94 s shorter than that of the traditional genetic algorithm by 21.26%. The experimental results show that this method has better performance in terms of path length and path repetition rate, and the arrangement of field traversal sequence and import and export can effectively reduce the path length and path repetition rate.

By using discrete artificial bee colony algorithm to search for the optimal traversal order of task target points, the agricultural robot can traverse all target points with minimum moving cost. At the same time, the discrete artificial bee colony algorithm is used to plan the cross-region connection path, and the shortest and collision-free walking path between the target points is found. In the traversal process of agricultural robot, the vertex of the zone closest to the end point of the previous farmland is selected as the starting point of this farmland, and then "round-trip" traversal planning is carried out along the long side, and finally the traversal path planning of the entire farmland map is realized.

CONCLUSIONS

In this study, a new DABC algorithm was proposed to effectively solve the field traversal problem of agricultural robots in hilly areas. Then, the effectiveness of the proposed algorithm was verified through simulation experiments. Finally, the main conclusions were drawn as follows:

(1) Given the small and densely distributed fields in hilly areas with obstruction by ridges between fields and no connected relations between fields, a method of establishing the connected relations between fields was proposed in this study, aiming to predict how agricultural robots will transfer to the next field after completing the coverage path of one field.

(2) A DABC algorithm was raised to solve the field traversal order planning problem. Following the idea of the adaptive strategy, the new algorithm transformed feasible solutions into food sources by means of path encoding. In the hired bee, observing bee, and scout bee stages, new food sources were generated by the algorithm based on the discrete crossover operator, reverse operator, and immune operator, and the algorithm performance was improved using the famous single/multi-step 2-opt local search algorithm. The MATLAB simulation experimental results showed that the average traversal path distance obtained by the improved genetic algorithm was reduced by 1.59% than that acquired through the traditional genetic algorithm.

(3) Through the comparative analysis of experiments, the field traversal order and the entrance and exit arrangement obtained by the proposed method can effectively reduce the path length and its repeatability, providing the superiority and feasibility of the proposed method. Meanwhile, the trajectory coordinates output by the algorithm can provide a reference for the large-area operations of agricultural machinery drivers or unmanned agricultural machineries. The follow-up study will focus on solving the challenges faced by intelligent algorithms in practical applications, especially online real-timeliness of navigation systems, Kalman linear filtering, etc.

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