ANALYSIS ON HANDLING PATH OPTIMIZATION OF AGRICULTURAL ROBOTS BASED ON IMPROVED ANT COLONY ALGORITHM
/
基于改进蚁群算法农业机器人搬运路径优化分析

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ABSTRACT

With the rapid development of agricultural machinery intelligence and informatization, agricultural robots are becoming the protagonist, promoting standardized production in agriculture, improving efficiency, and reducing labor costs. However, how to quickly plan an efficient and safe path for agricultural transport robots is currently a hot topic in path planning research. In this study, the path optimization problem of agricultural robots handling agricultural products (such as Edible Fungi) in and out of warehouses, which served as the study object, was solved. First, the number of agricultural handling robots was initialized based on the scanning method, and the geometric center of sub-path nodes was set as the virtual node. Secondly, the optimal path of the virtual node was solved using the improved ant colony algorithm embedded with a genetic operator, and the optimal result of sub-paths was acquired. Thirdly, the optimal solution meeting constraint conditions was obtained with the launch cost, transportation cost, and time cost of agricultural robots as objective functions. Lastly, the effectiveness of the optimization model and the improved ant colony algorithm was verified through the instance analysis. This study is of certain significance to the ex-warehousing path optimization of agricultural robots under the sustainable development concept of agricultural automation.

摘要

随着农业机械智能化和信息化的飞速发展，农业机器人正在成为主角，推动农业实现标准化生产，提高效率，减少人工成本。然而农业搬运机器人如何快速规划出一条高效、安全的路径是目前路径规划研究的热点问题。本文以农业机器人仓库运输路径优化为研究对象，解决农业机器人搬运农产品(例如食用菌)进出仓库场景下的路径优化问题。首先，基于扫描法初始化农业搬运机器人初始数量，并将子路径节点的几何中心设置为虚拟节点；其次，采用嵌入遗传算子的改进蚁群算法求解连接虚拟节点的最优路径，求解子路径的最优结果。第三，以农业机器人启动成本、运输成本和时间成本为目标函数，最终得到满足约束条件的最优解。最后，通过实例分析验证优化模型和改进蚁群算法的有效性，对农业自动化可持续发展理念下农业机器人出库路径的优化研究具有一定的意义。

INTRODUCTION

Agricultural robots refer to multi-degree-of-freedom autonomous operating equipment with sensing, decision-making, control, and execution capabilities for agricultural production, including an information perception system, a decision-making control system, an operation execution mechanism, and an autonomous mobile platform, namely “eyes, brain, hands, and feet”. At present, the labor force engaged in agricultural production in China is decreasing and the labor cost is increasing, so the demand for agricultural robots grows rapidly. In the future, with the development of urbanization, the rural labor force will continue to decrease. According to the characteristics and needs of agriculture, the research on agricultural robots has been carried out. A lot of research work has been done in autonomous tractors, small agricultural mobile platforms, grafting robots, loading robots, fruit sorting robots, picking robots, farmland information monitoring robots, and plant protection drones, which have been well applied in autonomous agricultural machinery, plant protection drones, and milking robots. China should vigorously promote the deep integration of informatization and industrialization, and speed up the process of intelligent production. As we all know, agricultural products warehouse is the key link in the circulation of agricultural products.

Improving the intelligent management level of workshops, tapping the potential, saving costs, and reducing energy consumption are topics of concern to both academia and industry.

With the rapid development of artificial intelligence and robot technology, agricultural robots are gradually replacing human beings to complete the task of handling agricultural products in and out of warehouses. `Driving path optimization of agricultural robots is the core problem encountered in the application of warehouse operations *(Li G H., 2021)*. In the environment with uncertain obstacles, the path planning of agricultural robots is the focus of research, that is, the collision-free path optimization from the starting point of movement to the target end point. When agricultural robots handle agricultural products in and out of a warehouse, the working environment directly affects their working state *(Jiang N. et al., 2020)*. Because agricultural product warehouses are generally characterized by narrow handling channels and many uncertain obstacles, the working efficiency of agricultural robots will often be reduced due to the poor optimization ability of path planning algorithms during dynamic path planning *(Yin J. et al., 2019)*. Therefore, robot path optimization algorithms have gradually become one of the research hotspots. Given this, agricultural robots were required to complete the task of handling agricultural products in and out of warehouses simultaneously, and the sum of robot start-up cost, transportation cost, and time cost was taken as the objective function to solve the modeling and algorithm research on the agricultural robot path optimization problem.

State of the art

The genetic algorithm (GA) is one of the earliest heuristic algorithms used to solve the path optimization problem of robots. *Panchu et al* solved the shortest time for robots to complete tasks using GA *(Panchu K P. et al., 2018)*. *Li et al* optimized the driving path of the robot based on the received dynamic information. Some scholars have also proposed to use GA to optimize the sequence of tasks to be completed by robots *(Li Y F. et al., 2014)*, to design an improved GA based on the roulette and optimal preservation strategy to solve the robot path optimization problem *(Qian Z. et al., 2015)*, and to use the dual-population genetic ant colony algorithm to solve the robot path problem *(Gang L I. et al., 2015; Pei Z B. et al., 2015)*. By analyzing the role of GA in solving the path optimization problem of robots, it is found that the algorithm can solve the optimal value problem of path optimization of small-scale robots, but its convergence speed is slow, failing to meet the agile demand of the workshop production mode. *Zhao et al* proposed to establish an interlocking relationship between α and β to define pheromone update rules *(Zhao H C. et al., 2018)*. Some scholars have proposed to solve the high-quality distribution route problem based on the ant colony algorithm *(Lu E H C. et al., 2016)*, and a hybrid ant colony algorithm has been put forward to solve the robot path optimization problem *(Kober J. et al., 2013)*. Based on the above analysis, it is found that the ant colony algorithm has obvious distribution characteristics, strong robustness, and high reliability when solving robot path optimization problems, but the disadvantage is that it will fall into a local optimal solution at a certain probability. In recent years, the reinforcement learning algorithm has also been applied to path optimization *(Polydoros A S. et al., 2017)*. Some scholars have designed an improved fuzzy Q learning algorithm to solve the problem of path planning strategies *(Duguleana M. et al., 2016)*. Some scholars have adopted the firefly optimization algorithm to solve the problem of vehicle path optimization *(Wang H F. et al., 2012)* and the tabu search algorithm to solve the problem of vehicle path optimization *(Wang C. et al., 2013)*. The above literature constructs the mathematical model of the robot carrying path respectively, selects different platforms to solve the robot path optimization problem, and most heuristic methods solve the path optimization problem of the carrying robot in the solution algorithm. The selection strategy of heuristic action improves the solution efficiency, and can obtain the optimal solution of the model. However, based on this, the path optimization search of the carrying robot has a high total distance and high consumption.

Some scholars have conducted in-depth research on the path optimization technology of handling robots in terms of technology, such as，*Faina, A. et al. (2020)* who describe the EvoBot modular design and through scientific experiments such as basic liquid handling, nurturing of microbial fuel cells, and droplet chemotaxis experiments document how functionality is increased in one module at a time with a significant amount of reuse. Gürel S. et al. studied the trade-off between cycle time and energy consumption of robots in robot units producing the same parts (*Gürel S. et al., 2019).* Gultekin et al. proposed a Second-order cone programming formula to find Pareto efficient solutions *(Gultekin et al., 2021)*.

A heuristic algorithm that can find a set of approximate Pareto efficient solutions was also developed, and the cone formula can find robot scheduling for small units with fewer machines in a reasonable computational time.

Santos et al solved the path optimization model of agricultural robots based on the point cloud transformation algorithm. When the robot encounters obstacles, the local path is re-planned through the point cloud transformation algorithm, thus improving the path safety of agricultural robots *(Santos L. et al., 2020)*. *Cernicchiaro et al* optimized the driving path of agricultural robots based on D* algorithm, and the example proved that the algorithm can improve the working efficiency of agricultural robots and shorten the movement time between execution points *(Cernicchiaro C. et al., 2019)*. *Azzabi et al* optimized the robot path based on the potential field method. In the process of moving, obstacles will repel the robot, which will help the robot avoid obstacles and improve the efficiency and safety of robot execution *(Azzabi A. et al., 2017)*. *Zhang et al* optimized the path of the robot by combining the improved ant colony algorithm and the potential field method *(Zhang Q. et al., 2019)*. The potential field method is used to plan the main path of the robot, and the improved ant colony algorithm to avoid obstacles and plan the path based on the main path. In addition, there are path planning strategies based on ant colony-particle swarm optimization *(Wang Z W. et al., 2018)*, robot path planning strategies based on longicorn search optimization algorithm *(Jiang X.Y. et al., 2014)*, and robot path planning strategies based on the improved longicorn search algorithm *(Xue J.K. et al., 2020)*. The above algorithms improve the robot path planning algorithm in terms of optimization accuracy, convergence speed, and running distance. In complex working environments, however, there are many breakpoints in the path of agricultural handling robots, and the path planning algorithm is prone to local optimization, slow convergence speed, and low result accuracy.

To sum up, Chinese and foreign scholars have made great achievements in robot path optimization research, mainly focusing on theories, models, and algorithms. However, there are few research results on multi-robot operation path optimization in the specific scenes of handling agricultural products in and out of warehouses simultaneously. In related research, meanwhile, intelligent bionic algorithms such as GA and particle swarm optimization have been mostly adopted, which, however, are generally subjected to low efficiency and slow convergence when solving the path optimization problem of robots. And the robot path optimization problem for agricultural product warehouses has been rarely solved using the improved ant colony algorithm. In the existing results, moreover, the path optimization problem under static environments has been mainly considered, not in line with the actual situation of many uncertain factors in agricultural product warehouses. Given this, this problem was solved in this study by proposing an ant colony algorithm embedded with a genetic operator. And the crossover and mutation mechanisms of the genetic operator were introduced to jump out of the local optimal solution combining the strong robustness and high reliability of the ant colony algorithm. In the meantime, the deficiency of a single algorithm was effectively compensated by organically combining GA and ant colony algorithm. The ant colony algorithm with a genetic operator could solve the driving path of agricultural handling robots, capture the dynamic collision information in agricultural product warehouse on the driving path, and realize dynamic obstacle avoidance. Finally, the path optimization problem with the objective of total cost minimization was solved.

MATERIALS AND METHODS

In the process of entering and leaving the agricultural product warehouse, each order contains different varieties and quantities of commodities. Therefore, agricultural robots need to pick according to the order requirements during the operation of entering and leaving the warehouse, and at the same time, complete the related tasks such as product warehousing. Otherwise, the inventory will increase, and even equipment shutdown will be induced, reducing inventory efficiency.

There is a certain physical distance between the product storage areas in the agricultural product warehouse, ensuring that the handling robot can shuttle back and forth and assume the position of each product storage location and the position of the warehouse-in and out operation area. The maximum load capacity of the agricultural handling robot is known, the maximum load capacity of the agricultural handling robot is greater than the weight or volume of products entering and leaving each cargo location each time, and each cargo location can only have one agricultural handling robot. Because the agricultural handling robot has strong dynamic endurance and the time window limit is not considered, the maximum running distance of the robot is no longer taken into account. According to the specific situation of the warehouse-in and out tasks of agricultural products, the number of agricultural handling robots is reasonably arranged. While completing the warehousing tasks of agricultural products, the objective function is to minimize the total cost of agricultural handling robots, such as start-up cost, transportation cost, and time cost. There is only one warehouse-in and out operation area in the workshop, and the robot returns to this operation area after completing the warehouse-in and out task, forming a closed running track, as shown in Fig. 1.

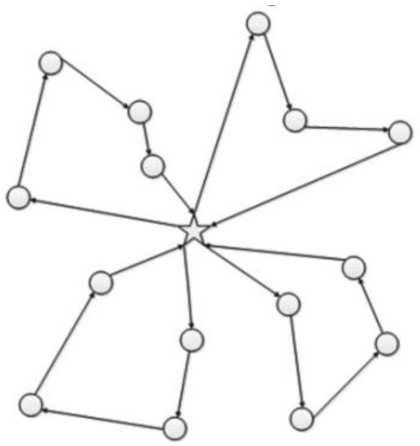

Fig. 1 - Schematic diagram of the running path of the agricultural handling robot

The robot sensor sends signals to the control system in time to adjust the distribution route. Therefore, considering the particularity of the warehouse environment and the problem of handling agricultural in and out of the warehouse, the dynamic obstacle avoidance problem was the main reason why the ant colony algorithm was improved by embedding a genetic operator in GA.

Model Building

In an agricultural product warehouse, there are R agricultural robots with the maximum load carrying capacity of Q that provide warehouse-in and out services for this warehouse. Therein, d_i stands for the warehouse-out quantity needed by the cargo location i; p_i is the warehouse-in quantity needed by the cargo location i; e_{ij} is the total warehouse-out quantity after the agricultural handling robot passes the cargo location i; f_{ij} represents the total warehouse-in quantity after the agricultural handling robot passes the cargo location i, and the sum of the warehouse-in and out quantities of the agricultural handling robot should not exceed its maximum load carrying capacity at any time; d_{ij} indicates the distance from the cargo location i to j, and the warehouse-in and out positions and the spatial position of each cargo location are already known and expressed by the corresponding coordinates; Q_{rij} is a decision variable, representing whether the agricultural handling robot r experiences a collision when moving from the cargo location i to j; both x_{ijr} and y_{ir} are decision variables defined as follows:

$$x_{ijr} = \begin{cases} 1, robot\ R\ moves\ from\ the\ cargo\ bay\ i\ to\ the\ j \\ 0, else \end{cases} \tag{1}$$

$$y_{ir} = \begin{cases} 1, Robot\ R\ to\ provide\ service\ for\ the\ Goods\ i \\ 0, else \end{cases} \tag{2}$$

The mathematical models for the agricultural robot's handling path optimization problem are as follows:

$$min \sum_i \sum_j \sum_r d_{ij} \times x_{ijr} \tag{3}$$

$$s.t.$$

$$\sum_{r=1}^{R} y_{or} = R \tag{4}$$

$$\sum_{i=1}^{M} y_{i0r} = 1(r = 1, \cdots, R) \tag{5}$$

$$\sum_{i=1}^{R} y_{ir} = 1(r = 1, \cdots, M) \tag{6}$$

$$\sum_{i=1}^{M} x_{ijr} = y_{jr}\ (j = 1, \cdots, M; r = 1, \cdots, R) \tag{7}$$

$$\sum_{j=0}^{M} x_{ijr} = y_{jr}\,(i=1,\cdots,M; r=1,\cdots,R) \tag{8}$$

$$\sum_{j=0}^{M} e_{ij} - \sum_{j=0}^{M} e_{ji} = p_i\,(i=1,\cdots,M) \tag{9}$$

$$\sum_{j=0}^{M} f_{ij} - \sum_{j=0}^{M} f_{ji} = d_i\,(i=1,\cdots,M) \tag{10}$$

$$e_{ji} + f_{ji} \le Q\sum_{j=0}^{R} x_{jir}\,(i,j=1,\cdots,M) \tag{11}$$

$$Q_{rij} = \begin{cases} 1, Collide \\ 0, else \end{cases} \tag{12}$$

In this model, Equation (3) represents the objective function, that is, the minimum warehouse-in and out cost; Equation (4) indicates that all robots start from the working area of the warehouse; Equation (5) means that the robot returns to the warehouse operation area after completing the task; Eqs (6), (7), and (8) indicate that only one robot arrives at a certain cargo location and provides services; Equation (9) represents the constraint on the quantity of agricultural products required by the warehouse; Equation (10) denotes the inventory constraint of products required by the warehouse; Equation (11) indicates the limit of the carrying capacity of the robot; in Equation (12), Q_{ij}=1 indicates whether the robot r experiences a collision when moving from the cargo location i to j, and Q_{ij}=0 means that no collision occurs.

Improved Ant Colony Algorithm

The position of a cargo location was acquired through the scanning method, i.e., its position was expressed by polar coordinates. The warehouse-in and out operation area of the warehouse served as the starting point, with its angle set to 0. Then, the equipment nodes were segmented with the robot's maximum carrying capacity as the constraint to obtain several subregions conforming to the carrying capacity limit.

The basic idea of the improved ant colony algorithm is described as follows: to solve the problem of pheromone shortage and slow convergence in the early stage of the ant colony algorithm, multiple feasible solutions are obtained by using GA in the initial stage, and the formula is transformed into an initial pheromone distribution. Then, the ant colony algorithm is used to further optimize the search and give full play to the positive feedback mechanism to facilitate the algorithm to converge quickly. In the pheromone update stage, high-quality solutions are selected from the candidate set using the Metropolis criterion of the simulated annealing algorithm, and only these high-quality solutions will update the pheromone concentration.

GA starts from the initial feasible solution, so it has a high convergence speed in the early stage. The process of obtaining the initial pheromone distribution by GA is as follows:

(1) Coding: According to the characteristics of the robot path optimization problem for handling agricultural products in and out of the warehouse, the real number coding method was adopted in this study, where the number 0 represents the warehouse-in and out operation area, and the numbers 1, 2, 3, and n represent the positions of goods. The number of robots in and out of the warehouse was set to k, so the chromosome length should be set to $k+n+1$, so that all customer points could be served in extreme cases. The code $0, i_1, \cdots, i_e, 0, i_f, \cdots, i_k, 0$ represents a possible chromosome.

(2) Population initialization: A total of n cargo locations were arranged randomly, the number 0 was inserted in the arrangement according to the model constraint, and another number 0 was added to the starting point and end point to indicate that both the robot's starting point and end point were inside and outside the warehouse operation area. Then, a chromosome (a feasible solution) was generated. This process was repeated m times, where m stands for the population.

(3) Determination of the fitness function: The objective function $minz$ of the path optimization model for robots handling agricultural products was achieved at the minimum total cost. Since the fitness function was in a direct proportion to the individual survival rate, the fitness function value was determined in this study as seen in Equation (13).

$$f = 1/ minZ \tag{13}$$

(4) Improved selection operation. In this study, the population was selected by means of roulette selection, and the principle of steady-state replication was introduced based on the traditional roulette selection method so as to skip the links of crossover and mutation and directly enter the next iteration, thereby ensuring that the optimal gene of each generation would not be lost.

(5) Crossover operation. The crossover operation was completed through multiple rounds of selecting crossover individuals, and a random number rand was generated between crossover individuals in each round. If the random number rand was less than the crossover probability, the genetic crossover operation was carried out by using two-point crossover. However, an infeasible solution might be generated by the direct crossover operation, as shown in Fig. 2, and two new offspring chromosomes were obtained. The two offspring were illegal solutions: gene 0 appeared twice in offspring A, but gene 3 did not exist; gene 3 appeared twice in offspring B, but gene 0 did not exist. On this basis, to avoid the direct crossover of infeasible solutions, the following idea was adopted in the implementation of the algorithm: for example, when the offspring $A1$ was obtained, the first three genes A (1-3):012 and the last three genes A(8-10): 789 of the parent A were kept unchanged, while the 6 genes retained in A were deleted in the parent B in turn, leaving 4 genes B(4): 6543 in B, then the offspring $A1$= A(1-3)+ B(4)+ A(8-10) was acquired, namely A1:0126543789, and the offspring $B1$ could be obtained similarly.

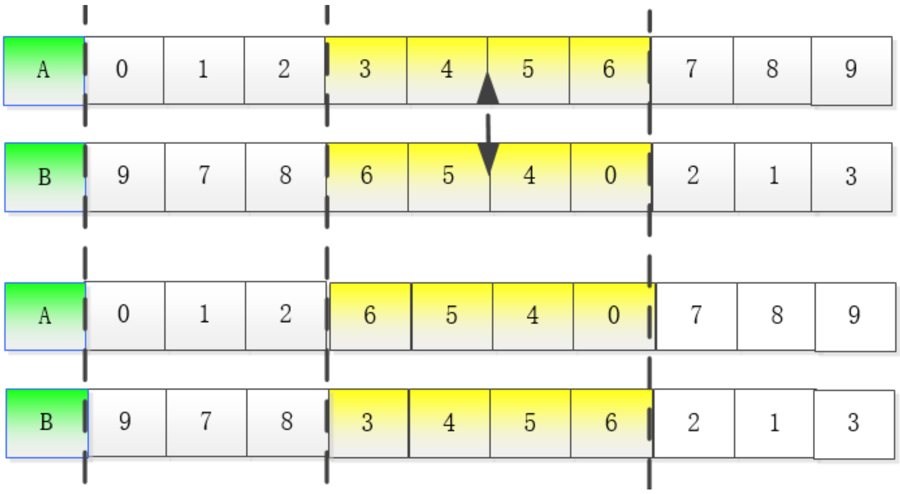

Fig. 2 - Schematic diagram of chromosome crossover operation

(6) Mutation operation. According to the probability of the mutation operation, the result of Step (5) was subjected to the mutation operation, which was specifically implemented by local reversed order.

(7) Generation of an initial pheromone distribution. When the set evolutionary generation Gen_{max} was reached, the iteration was terminated, the solution obtained at this time was regarded as the initial solution of the ant colony algorithm, and the initial concentration of pheromones on each path was calculated according to Equation (14).

$$\tau_{ij} = \sum_{k=1}^{m} \frac{Q}{L_k} \tag{14}$$

where the additional strength coefficient of pheromones is usually set as a constant, which is expressed by Q; the total length of ant k's walking route in this iteration is expressed by L_k.

After the initial pheromone distribution was generated, the ant colony algorithm was used to further optimize the search and generate the candidate set route, which had a common solution. Then, the pheromone concentration on the path needed to be updated.

If the pheromone was updated by the global method without considering the quality of the solution, the pheromone concentration on the better path and the worse path would not be much different, which then interfered with the subsequent optimization search of ants, led to a large number of invalid handling paths in the search, and then affected the convergence speed of the algorithm.

Therefore, after the candidate set Routh was obtained, the Metropolis criterion of the simulated annealing algorithm was introduced to filter the solutions of the candidate set, and a high-quality solution set Routh_New was generated, and only the pheromone concentration was updated.

Firstly, the objective function value z_i of candidate set solutions was calculated one by one; then, according to the acceptance probability formula of the simulated annealing algorithm, as shown in Equation (15), whether the current solution was added to the latest solution set was determined.

$$P_i = \begin{cases} 1, & z_i < z_{best} \\ exp(-\frac{z_i - z_{best}}{kT}), & z_i \geq z_{best} \end{cases} \tag{15}$$

where the objective function value of the robot's optimal driving path is expressed by z_{best}; the current temperature value of the simulated annealing algorithm is expressed by T, which decreases at a certain proportion as the iteration process of the ant colony algorithm continues; k is a constant. When $z_i<z_{best}$, this solution is directly added to the latest set. When $z_i>z_{best}$, a random number rand between $(0,1)$ is generated. If $rand < \exp(-\frac{z_i - z_{best}}{kT})$, this solution is added into the latest set. At high temperature, the greater the T value, the greater the calculation result of $\exp(-\frac{z_i - z_{best}}{kT})$. In this way, more high-quality solutions in the candidate set will be added to the *Routh_New* solution set, thus increasing the diversity of understanding and avoiding prematurity and stagnation to some extent. At low temperature, if the value of $\exp(-\frac{z_i - z_{best}}{kT})$ is small, the calculation result is small, which reduces the number of high-quality solutions added to the *Routh_New* solution set, thus accelerating the convergence speed of the algorithm.

When the value of ρ—an important factor affecting the pheromone concentration on the handling path of agricultural robots—is small, the pheromone evaporation speed is slow, which leads to too many pheromone residues on the handling path of agricultural robots, expands the search range of ant colony, and produces a large number of invalid paths, which in turn leads to the slow convergence speed of the ant colony algorithm. When the evaporation factor ρ is too large, the pheromone on the path evaporates rapidly, and the pheromone concentration difference between the better path and the worse path is obvious, which narrows the search range of the ant colony and makes the ants gather on the better path quickly. In the early search, the main purpose is to get the optimal solution as soon as possible, so a larger value of ρ should be taken. When the algorithm is at a standstill, it may fall into a local optimal solution. At this time, it is necessary to reduce this value, expand the search range of the ant colony, and jump out of the local optimal solution.

Based on the above analysis, the numerical formula in this study is displayed in (16).

$$\rho(t+1) = \begin{cases} max[0.7 * \rho(t), \rho_{min}], & x = x_{max} \\ \rho(t), & else \end{cases} \tag{16}$$

where:

x stands for the number of consecutive cycles of the optimal solution;

x_{max} is a constant value, and the minimum value of ρ is expressed as ρ_{min}.

To avoid too much attenuation of ρ from influencing the algorithm performance, a limit is added to ρ_{min}.

When $x=x_{max}$, the value of ρ is reduced based on $0.7\rho(t)$, and x is set to 0, followed by counting again. Such cycles are continued until ρ attenuates to the minimum value ρ_{min}.

The flow of the improved ant colony algorithm solving the optimization model in this study is shown in Fig. 3.

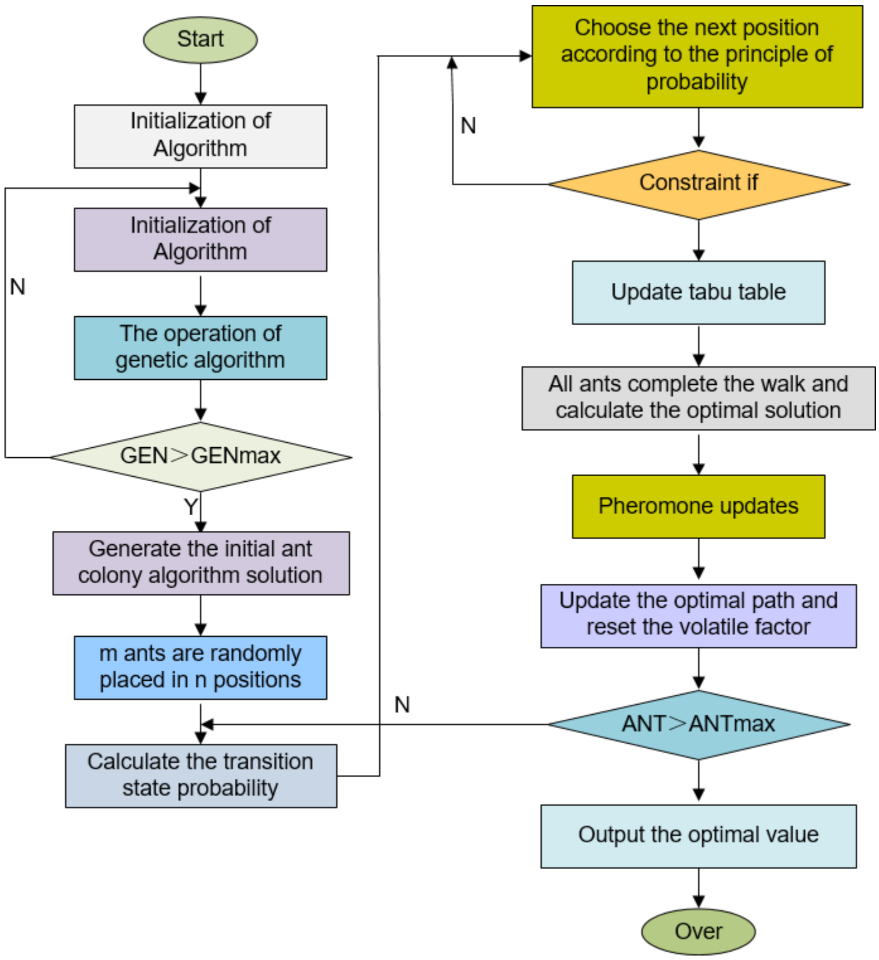

Fig. 3 - Flowchart of the improved ant colony algorithm for solving the optimization model

RESULTS

Experimental Environment and Parameter Setting

In this study, Intel i7 processor and Matlab2014b were adopted for the experiment. The mutation probability, crossover probability, and genetic gap of GA were 0.1, 0.9, and 0.7, respectively. In the ant colony algorithm, the important factor of pheromone was 1, the constant coefficient Q was 1, the evaporation factor of information was 0.1, and the important factor of the heuristic function was 5. The discount factor and learning rate of the reinforcement learning algorithm were 0.9 and 0.2, respectively. The three cost parameters are listed in Table 1.

Table 1

Cost parameters

Parameter type	Parameter name	Value
Basic cost	Basic cost of dispatched robots	300 yuan (CNY)
Transportation cost	Unit distance loss of robots	5 yuan (CNY)
	Robot operating speed	10 m/min
Time cost	Robot handling/unloading time	1 min
	Maximum carrying capacity of robots	200 kg

In this study, the operation area inside and outside the agricultural product warehouse served as node o with coordinates of (40,50). In the warehouse, there were 29 cargo locations, which were expressed by the corresponding coordinate values X and Y, and the number of agricultural products in and out of each cargo location was known, as seen in Table 2.

Table 2

Warehouse-in and out information of cargo locations

Cargo location No.	Coordinate X	Coordinate Y	Warehouse-out quantity	Warehouse-in quantity	Cargo location No.	Coordinate X	Coordinate Y	Warehouse-out quantity	Warehouse-in quantity
0	40	50	0	0	13	22	75	15	15
1	45	68	4	6	14	22	85	6	4
2	45	70	10	20	15	20	80	17	23
3	42	66	7	3	16	20	85	16	24
4	42	68	8	2	17	18	75	10	10
5	42	65	4	6	18	15	75	8	12
6	40	69	2	18	19	15	80	7	3
7	40	66	11	9	20	30	50	8	2
8	38	68	12	8	21	30	52	18	2
9	38	70	6	4	22	28	52	3	17
10	35	66	4	6	23	28	55	2	8
11	35	69	7	3	24	25	50	1	9
12	25	85	10	10	25	25	52	31	9

Experiment and Comparative Analysis

In this study, the warehouse-in and out path optimization model for agricultural handling robots was solved using the improved ant colony algorithm embedded with a genetic operator, the maximum number of iterations was set to 200, and the start-up cost of agricultural handling robots was 300 yuan. A satisfying solution could be obtained by solving the model, namely, the warehousing and unloading task of agricultural products was completed needing three mobile robots, the total travel distance of robots was 191.81 m, and the total cost was 1533.61 yuan (CNY). To complete the task of agricultural product delivery and improve the ant colony algorithm, 3 robots are required, and the driving path of each robot is shown in Figure 3. This algorithm took 448.81 s. The path diagram of the improved ant colony algorithm embedded with GA is displayed in Fig. 4. The convergence curve of the improved ant colony algorithm embedded with GA is exhibited in Fig. 5, and the calculation results are listed in Table 3.

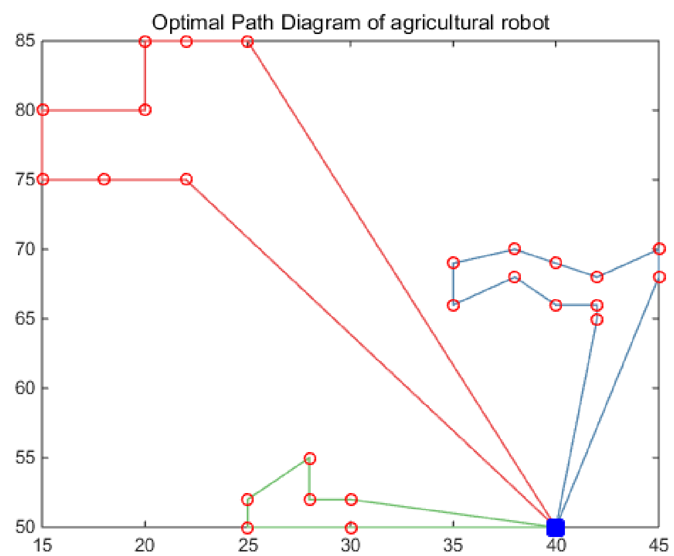

Fig. 4 - Path diagram of the ant colony algorithm embedded with GA

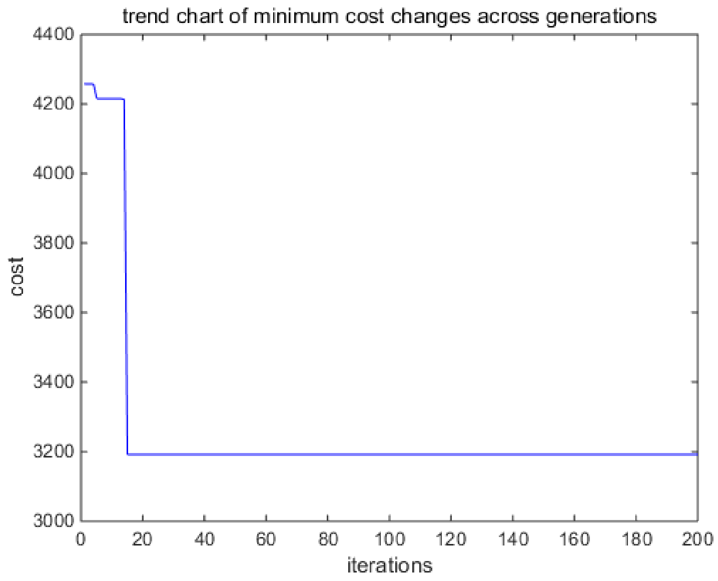

Fig. 5 - Convergence curve of the improved ant colony algorithm embedded with GA

Table 3

Optimal service path (improved ant colony algorithm)

Service path	Actual carrying capacity	Maximum carrying capacity	Full load rate
0→5→3→7→8→10→11→9→6→4→2→1→0	160	200	80%
0→13→17→18→19→15→16→14→12→0	170	200	85%
0→20→24→25→23→22→21→0	110	200	55%

To further verify the effectiveness of the ant colony algorithm embedded with a genetic operator, the traditional ant colony algorithm was also designed in this study to solve the model. Under the constant initial cost and parameters, a total of 4 mobile robots were required to solve the agricultural robot path optimization model, with a total driving distance of 277.32 m, a total cost 2004.64 yuan (CNY), and time consumption of 604.48 s. To complete the task of agricultural product delivery, the traditional ant colony algorithm requires four robots, and the driving path of each robot is shown in Figure 6. The path diagram of the traditional ant colony algorithm is displayed in Fig. 6, the convergence curve of the traditional ant colony algorithm is displayed in Fig. 7, and the calculation results are listed in Table 4.

Compared with the traditional ant colony algorithm, the improved ant colony algorithm embedded with a genetic operator displayed strong exploration and convergence, accompanied by a better objective function value. The comparison of the two algorithms is shown in Table 5.

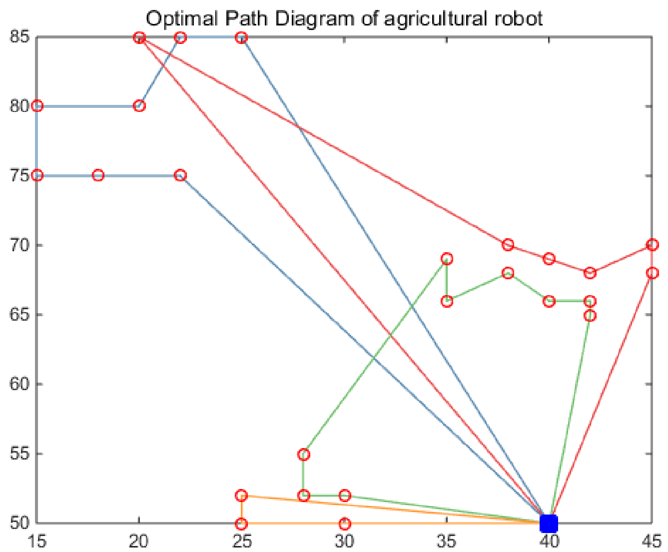

Fig. 6 - Path diagram of the traditional ant colony algorithm

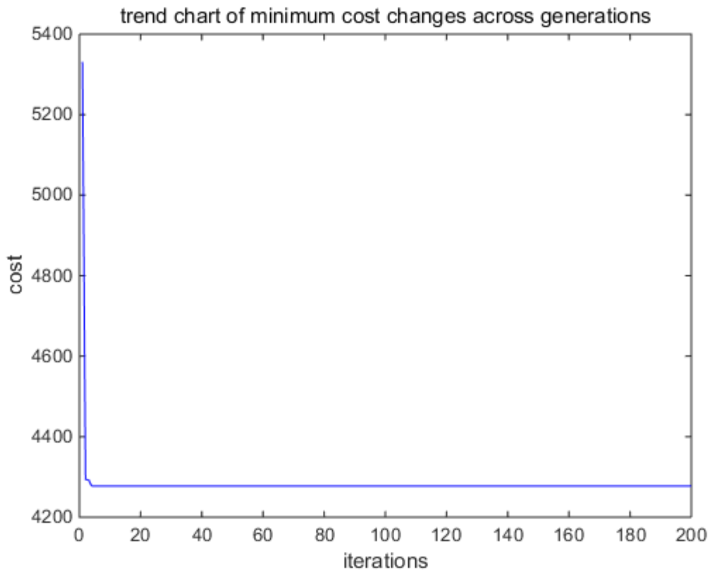

Fig. 7 - Convergence curve of the traditional ant colony algorithm

Table 4

Optimal service path (ant colony algorithm)

Service path	Actual carrying capacity	Maximum carrying capacity	Full load rate
0→13→17→18→19→15→14→12→0	150	200	75%
0→16→9→6→4→2→1→0	120	200	60%
0→5→3→7→8→10→11→23→22→21→0	130	200	65%
0→20→24→25→0	60	200	30%

Table 5

Comparison of the two algorithms

Algorithm	Number of robots	Average full load rate	Driving distance (m)	Total cost (yuan, CNY)	Algorithm time consumption (s)
Improved ant colony algorithm	3	73.33%	191.81	1533.61	448.81
Traditional ant colony algorithm	4	57.5%	277.32	2004.64	604.48

From Table 5, it can be seen that the improved ant colony algorithm embedded with a genetic operator is superior to the traditional ant colony algorithm in the number of robots, average full load rate, driving distance, total cost, and time consumption. The traditional ant colony algorithm needs 4 robots to complete the task of handling agricultural products in and out of the warehouse, while the improved ant colony algorithm embedded with a genetic operator only needs 3 robots to complete the same task, which improves the efficiency by 25%.

The average full load rate of agricultural robots obtained by the traditional ant colony algorithm is 57.5%, while that by the improved ant colony algorithm embedded with a genetic operator is 73.33%, with an increase of 15.83%. In terms of robot driving distance, the total driving distance of agricultural robots obtained by the traditional ant colony algorithm is 277.32 m, while that by the improved ant colony algorithm embedded with a genetic operator is 191.81 m. The total cost of agricultural robots obtained by the traditional ant colony algorithm is 2004.64 yuan, while that by the improved ant colony algorithm embedded with a genetic operator is 1533.61 yuan. In terms of time consumption, the convergence time of the traditional ant colony algorithm is 604.48 s, while that of the improved ant colony algorithm embedded with a genetic operator is 448.81 s, indicating an efficiency improvement of 25.75%.

CONCLUSIONS

In the process of large-scale transfer of rural surplus labor force, the shortage of young labor force and strong labor force has gradually become prominent in the field of agricultural production. Since the appearance of agricultural robots, both speed and variety have developed very well, which has gradually changed the traditional agricultural labor method and improved the level of agricultural modernization. However, many problems have been exposed in the wide application of agricultural robots. On this basis, the path optimization problem of moving robot entering and leaving warehouse is studied. In addition, an ant colony algorithm embedded with genetic operators is designed to optimize the path of agricultural transport robots. The main findings are as follows:

(1) Establish an optimization model, and establish a path optimization model of agricultural handling robot with full consideration of start-up cost, transportation cost and time cost. The simulation results show that the optimized model can achieve lower overall delivery cost.

(2) Algorithm optimization. An ant colony algorithm embedded with genetic operator was proposed to solve the path optimization problem of agricultural product handling robot in agricultural product warehouse. By using sequence decision making and reinforcement learning environment perception, pheromone initialization effectively improves the problem of insufficient initial pheromone in ant colony algorithm. The Metropolis pheromone update strategy proposed in this paper can accelerate the convergence of the algorithm while ensuring the quality of the solution.

(3) Algorithm performance comparison. By comparing the improved ant colony algorithm with the traditional ant colony algorithm, it is verified that the ant colony algorithm with genetic operator embedded in this study can effectively reduce the comprehensive allocation cost and has high convergence efficiency.

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