MULTI-UAV TASK ALLOCATION AND PATH PLANNING METHOD FOR AGRICULTURAL PATROL SCENE

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面向农业巡检场景的多无人机任务分配与路径规划方法

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ABSTRACT

A multi-unmanned aerial vehicle (UAV) task allocation and path planning model with the maximum endurance constraint was constructed specific to the agricultural patrol scene. Moreover, an optimized ant colony optimization (ACO) algorithm applicable to grid map environment was proposed given such problems of the traditional ACO algorithm as limited path search direction and field of view, failure to find the shortest path and proneness to deadlock. This method preprocessed the grid map environment, extracted the feature points of obstacles, and selected such feature points as the way-finding access nodes; then, the construction efficiency of the solution was enhanced via the nonuniform pheromone distribution based on ACO algorithm, the guiding function of path search was strengthened using Tent chaotic mapping, and the pheromone evaporation coefficient was dynamically adjusted to prevent the algorithm from too early convergence. The experimental results show that the proposed method more conforms to the operational requirements of rotary-wing UAVs with limited cruising ability in comparison with the existing methods. Besides, the convergence efficiency of the improved ACO algorithm embedded with the niche genetic algorithm is 30.55% higher than that of the traditional ACO algorithm. The experimental results verify the practicability and effectiveness of the proposed method.

摘要

针对农业巡检场景的多无人机任务分配与路径规划问题，构建一种最大航程约束的多无人机任务分配与路径规划模型。针对传统蚁群算法存在的路径搜索方向和视野受限、无法找到最短路径、容易发生死锁等问题，提出了一种适用于网格地图环境下的优化蚁群算法。该方法对网格地图环境进行预处理，提取障碍物的特征点，并选择这些特征点作为寻路访问节点; 然后，基于蚁群算法，采用信息素不均匀分布来提高解的构造效率，采用 Tent 混沌映射增强路径搜索的引导作用，动态调整信息素挥发系数以避免算法过早收敛。实验结果表明，提出的方法相比于现有方法更符合续航能力有限的旋翼无人机作业需求，且相比于传统蚁群算法，提出的嵌入小生境遗传算法的改进蚁群算法与传统蚁群算法相比，算法收敛效率提升 30.55%。实验结果证明了所提方法的实用性和有效性。

INTRODUCTION

In the development process of modern agriculture, agricultural intelligent patrolling unmanned aerial vehicles (UAVs) are becoming an important force to promote agricultural production efficiency, environmental protection and intelligence. These UAVs are equipped with advanced sensing technology and artificial intelligence system, which can quickly and accurately patrol farmland and collect and analyze key data *(Ning and Zhao., 2019)*. As the level of agricultural mechanization is continuously elevated, UAVs have been widely applied to various agricultural fields, and good path planning serves as the technical support for autonomous flight *(Duan and Wang, 2004)*. With the constant scientific and technological development, UAVs have been extended to a lot of industries, while their movement cannot be separated from path planning. So-called path planning refers to finding the path along which UAVs can safely reach the destination from the starting point according to the requirements of the fastest speed and the lowest energy consumption under known or unknown environmental information *(Dong et al., 2023)*. This kind of planning can be divided into global path planning and local path planning. In this study, the global path planning problem under static environment is mainly considered.

Multi-UAV patrol for agricultural patrol scene is one of the important means of ensuring the stable operation of agricultural systems. Facing the agricultural patrol scene, rotary-wing UAV patrol instead of manual patrol integrates the merits of high safety, low cost, strong operability and high accuracy *(Kong et al., 2023)*. However, single UAVs are of limited cruising ability, failing to efficiently complete the electricity patrol task on a large scale, which, however, can be generally achieved by multi-UAV collaborative operation. Therein, multi-UAV task allocation and path planning are crucial technical challenges *(Yu et al., 2023)*. First, UAV groups need to perform reasonable patrol task allocation, contributing to the shortest time spent in completing the patrol task or the shortest flight distance. Second, UAVs must evade obstacles in the environment, ensuring that UAVs can safely execute the patrol task.

In most of the existing studies, multi-UAV task allocation is considered separately from path planning. A classical task allocation method, ant colony optimization (ACO) algorithm, can provide the optical allocation scheme under most circumstances *(Corregidor-Castro et al., 2021)*. In addition, biological intelligence methods have also been extensively used to solve the task allocation problem *(Palomaki et al., 2017)*. However, all the above methods belong to centralized settings. Despite the simple logic, they are inapplicable to large-scale task allocation. Different from centralized allocation methods, distributed task allocation methods can usually achieve high calculation efficiency and acceptable distribution schemes *(Baik and Valenzuela, 2021)*. Market auction-based methods have been highly concerned since it can balance the computational complexity and solving quality very well *(Sun et al., 2019)*. Such methods complete task allocation by driving UAVs to receive the prices offered by all neighbors. In a recent study, *Doull et al. (2021)* put forward a distributed task allocation algorithm by introducing the alternating direction method of multipliers (ADMM), and experimentally proved that the proposed method can harvest the best convergence under most circumstances. Although the above market auction-based methods can rapidly provide acceptable task allocation schemes, they have not considered the path planning problem, making it necessary to solve the obstacle avoidance path of UAVs via path planning algorithms after obtaining the task allocation scheme *(Avendaño-Valencia et al., 2021)*. In addition, multi-UAV task allocation and path planning have been simultaneously considered by some methods. Aiming at logistics distribution scene, *Xu et al. (2020)* added the collision constraint of UAVs into the objective function to solve the problems of multi-UAV task allocation and path planning. *Dulava et al. (2015)* considered the problems of multi-UAV task allocation and motion planning under dense obstacle scene. Zhu and Wang *(2020)* introduced three-dimensional Dubins curve to disperse the heading angle of UAVs, and solved it by integrating task allocation and path planning. *Hayes et al. (2020)* put forward a joint optimization method of task allocation and path planning for balancing resources. However, the above methods either do not consider the coupling problem between task allocation and path planning, or do not consider obstacle avoidance in the environment. In fact, multi-UAV task allocation and path planning constitute a mutually coupling problem, so they must be considered as a whole. *Zhao et al. (2021)* introduced Dubins curve, considered the heading angle of UAVs, and solved the problems of task allocation and path planning by combining ACO and self-organizing map (SOM) algorithm. *Coombes et al. (2020)* estimated the length of UAVs' obstacle avoidance path using the improved A*algorithm and solved the coupling problem of task allocation and path planning. Hodgson *et al. (2018)* introduced vector direction to modify UAV's direction of motion and realize their automatic obstacle avoidance, and completed task allocation in combination with SOM method. *Ullah et al. (2022)* solved the problems of air-land collaborated task allocation and path planning through improving mixed integer linear programming (MILP) method and genetic algorithm (GA). Nevertheless, the above methods are faced with the bottleneck of slow solving speed and it is difficult to ensure the real-timeliness of the system in large-scale multi-UAV patrol scene. In addition, large-scale open environment usually needs to be considered to solve the problems of task allocation and path planning in electricity patrol scene. Due to the cruising ability limitation of rotary-wing UAVs, the maximum endurance constraint of UAVs must be taken into account in task allocation. However, the problems of task allocation and path planning under electricity patrol have been rarely directly considered by the existing methods. Although some methods have considered the maximum endurance constraint of UAVs, they give solutions slowly or fail to consider environmental obstacles.

The battery capacity of UAVs is limited, which leads to their weak cruising ability and failure to execute long-time large-scale patrol tasks. Hence, how to realize efficient patrol by taking full use of limited capacity has become an important challenge faced in electric transmission line patrol. In the patrol process of UAVs, the patrol time and energy consumption are mainly related to the trajectory design of UAVs. In reality, UAVs will start from the nest/service center, fly to the patrol region for data collection and finally return to the nest/service center. To improve the patrol efficiency of UAVs, the distance or energy consumption for UAVs to execute tasks has been reduced in relevant work by optimizing the trajectory of UAVs *(Zeng et al., 2019)*.

Chabot and Francis (2016) considered the convex polygonal coverage path planning and designed a path planning algorithm with low energy consumption on the premise of meeting the resolution of patrol images. *Huang et al. (2023)* put forward an accurate honeycomb decomposition method to seek for the least number of turning times in UAV coverage path planning. *Jones et al. (2021)* put forward a path planning algorithm of energy aware coverage, which reduced energy consumption by optimizing the trajectory of UAVs and their patrol speed. *Linchant et al. (2015)* minimized the energy consumption in the patrol process by optimizing the trajectory, flight speed and resource allocation of UAVs. *Chung et al. (2021)* proposed a reinforcement learning-based UAV trajectory design method, which dynamically adjusted the trajectory through multiple UAV-environment interactions and solved the non-convexity of the problem, but it failed to obtain the optimal trajectory or radically solve the trajectory optimization problem of UAVs. In relevant literature regarding patrol scene, the system energy efficiency *(Cao et al., 2019)* and sensing performance have been improved by optimizing the trajectory and resource allocation of UAVs. *Bowley et al. (2019)* proposed a continuous trajectory design scheme of networked UAVs based on TD3 to minimize the patrol time of UAVs with communication constraints satisfied. Facing the challenge of energy limitation of UAVs, *Qayyum et al. (2020)* minimized the energy consumption of UAV patrol by jointly optimizing the trajectory of UAVs, sensor data unloading and sensor wireless energy transmission. *Augustine and Burchfield (2022)* proposed a routine inspection system for UAVs driven by mobile edge computing to solve the challenge of providing effective data perception and automatic transmission for wind turbine inspection. While ensuring the accuracy of data, it minimized the energy consumption of UAVs by jointly optimizing the trajectory and calculating operation. Aiming at the central requirements for efficient danger detection and disaster management in the future network physical system of intelligent patrol nodes, *Wang and Zhang (2017)* put forward a new path planning algorithm for autonomous inspection of large-scale geographic regions and considered all aspects of energy consumption for UAV groups during inspection, including the energy required by flight, hovering and data transmission. The results show that the path planning problem can be effectively solved within polynomial time. When designing the patrol trajectory of UAVs, the returning of UAVs to the nest for charging in actual patrolling process has not been taken into account, but instead, it is generally assumed that UAVs have enough energy in the process of patrolling. In fact, however, the single endurance of UAVs will fail to support the completion of all patrol tasks when the number of patrol points exceeds a certain value.

Based on the above discussion, such problems of the traditional ACO algorithm as limited path search direction and field of view, failure to find the shortest path and proneness to deadlock and unsmooth path were mainly considered in this study. Given these problems, a task application and path planning method facing the agricultural patrol scene was proposed, which solved the coupling problem of path planning and task allocation while considering the maximum endurance constraint of UAVs. Moreover, the following improves were made: (1) The grid map environment was preprocessed, i.e., extracting feature points; (2) in the process of path search, these feature points were used as path nodes; (3) on the basis of such feature points, path planning was performed through the improved nonuniform pheromone distribution, two-way parallel path search, Tent chaotic mapping and the dynamic adjustment of the pheromone evaporation coefficient.

MATERIALS AND METHODS

Problem description

In the agricultural patrol scene, it is assumed that a nest (a vehicle parked on the UAV parking platform, which can accommodate multiple rotary-wing UAVs) is responsible for one patrol region. After completing patrol task allocation in the nest, UAVs start flying to the maintenance region, access patrol tasks allocated one by one, and autonomously fly back to the nest after completing such tasks. During the flight process, UAVs need to bypass no-fly zones like buildings, trees and electromagnetic field interference and ensure that the flight distance should be as short as possible. It is noteworthy that since all patrol tasks are implemented on ground, UAVs were assumed to fly according to a constant height during the flight process, and thus task allocation and path planning were carried out in 2D space.

Mathematical model

$U=\{1, 2, \ldots, i, L, m\}$ is set as the index set of UAVs in the nest, where m represents the number of UAVs. $T = \{1, 2, \cdots, j, \cdots, n\}$ is set as the index set of n patrol tasks in the patrol region. Without loss of generality, v_j is defined as the importance factor of task j. Since each patrol task has the same priority in this study, $v_j = 1$. λ_l denotes the distance discount factor.

To guarantee the monotonic decrease of the optimized objective function, $\lambda_l < 1$ should be met, and better solving quality could be achieved if $\lambda_l = 0.9$ was empirically taken in this study. According to the literature *Yang et al. (2020)* the total reward value $f_i(T_i)$ for all tasks in the patrol task set T_i accessed by UAV can be expressed by Equation (1).

$$f_i(T_i) = \sum_{j=1}^{|T_i|} \nu_j \lambda_l^{d(Path_i^j)} \tag{1}$$

where $|\bullet|$ is the number of elements in the set; $T_i (T_i \subseteq T)$stands for the patrol task set allocated to UAV i according to the access sequence; $Path_i$ is the shortest obstacle avoidance path for the task set T_i accessed by the UAV; $Path_i^j$ is the sub-path of $Path_i$, indicating the path for UAV *i* to access the task $j(\forall j \in T_i)$; $d(Path_i^j)$ is the length of the sub-path $Path_i^j$.

During the process of task allocation, the undistributed task k is added into the set T_i to obtain the marginal reward value $\omega_i(k)$ of the UAV i, as seen in Equation (2):

$$\omega_i(k) = f_i(T_i \cup \{k\}) - f_i(T_i), \forall k \in T, k \not\subset T_i \tag{2}$$

Therefore, the expression of $\omega_i(k)$ can be acquired by combining Equations (1) and (2), as seen in Equation (3).

$$\omega_i(k) = \sum_{j=1}^{|T_i \cup \{k\}|} \nu_j \lambda_l^{d(Path_i^j)} - \sum_{j=1}^{|T_i|} \nu_j \lambda_l^{d(Path_i^j)}, \forall k \in T, k \not\subset T_i \tag{3}$$

where $\omega_i(k)$ ensures that the objective function is a submodular function, which has a significant attribute of progressive decrease in marginal gain, i.e., the more the tasks allocated to the UAV *i*, the smaller the marginal gain $\omega_i(k)$ obtained by the UAV through selecting the patrol task k. The convergence of the algorithm is ensured by the progressive decrease attribute of the marginal gain *(Baik et al., 2021)*.

To sum up, the total reward function for all UAVs to complete task allocation can be described by Equation (4).

$$\begin{cases} max \sum_{i=1}^{|U|} \left(\sum_{j=1}^{|T_i|} x_{ij} \cdot v_j \cdot \lambda_q^{d(Path_i^j)} \right) \\ s.t. |T_i| \le L_i, \forall i \in U \\ \sum_{i=1}^{|U|} (x_{ij}) = 1, \forall j \in T \\ d(Path_i) \le D_{max}^i, \forall i \in U \end{cases} \tag{4}$$

where x_{ij} means that if the task *j* is allocated to the UAV i, $x_{ij} = 1$, or otherwise, $x_{ij} = 0$. The constraint condition is described as follows: the number of tasks allocated to each UAV does not exceed the maximum number of tasks $L_i$accessed by the UAV; each task is only allocated to one UAV, while one UAV can be allocated with multiple tasks; the length of the obstacle avoidance path for UAVs to execute patrol tasks should not exceed their maximum endurance D_{max}^i.

Principle of ACO algorithm

As a swarm intelligence algorithm, ACO refers to the intelligent behavior exhibited by a group of non-intelligent or slightly intelligent individuals through collaboration, providing a new possibility for solving complex problems *(Kong et al., 2023)*. ACO was first proposed by Italian scholars *Colorni A., Dorigo M. et al.* in *1991*. Through two decades of development, ACO algorithm has achieved enormous progress in theoretical and applied research *(Doull et al., 2021)*. ACO algorithm, a bionics algorithm, is enlightened by ant foraging behavior in nature *(Ullah et al., 2022)*. During foraging in nature, ant colonies can always find one optimal path from the ant nest to the food source. The optimization mechanism of ACO algorithm, which is a new intelligent optimization algorithm, is divided into adaption stage and collaboration stage. When efforts are made to obtain the optimal solution, ACO dynamically optimizes the objective function from an unordered state to an ordered state.

The actual behavior of ants was simulated through a multi-UAV task allocation and path planning model specific to the agricultural patrol scene, and the definitions were presented as follows: m stands for the number of ants; d_{ij} is the distance from the patrol point *i* to *j*, and $d_{ij} = \{i, j = 1, 2, \cdots, n\}$; τ_{ij} is the pheromone concentration between patrol points; ρ is the pheromone attenuation factor, which is an adjustable parameter within [0,1]; η_{ij} represents the heuristic factor of the edge, also referred to as visibility, and$\eta_{ij} = 1/d_{ij}$;

P_{ij}^k indicates the probability for ant k to move from patrol point i to j; $tabu_k$ is the patrol point currently passed by ant k; $allowed_k$ denotes the patrol point where ant k can choose to move, and $allowed_k = \{0,1,2,3,\cdots,m\} - tabu_k$. β is the influence coefficient of expected heuristic factor on the selected path during the movement of ants; α is the influence coefficient of pheromone on the selected path.

At initial moment, the pheromone on each path is equal, i.e., $\tau_{ij} = C$ (C is a constant). The direction of ant motion $k(k = 1,2,3,\cdots,m)$ depends on the pheromone on the selectable path under the current state. In this case, the random proportion rule serves as the transfer rule of the ant system, and the probability for ants to transfer to the selectable path is displayed in Equation (5).

$$P_{ij}^k = \begin{cases} \dfrac{\tau_{ij}^{\alpha}(t)\cdot\eta_{ij}^{\beta}(t)}{\sum\limits_{s\in \text{allowed}_k} \tau_{is}^{\alpha}(t)\cdot\eta_{is}^{\beta}(t)}, j \in \text{allowed}_k \\ 0,, else \end{cases} \tag{5}$$

Ants select the next patrol node at patrol node i, as seen in Equation (6).

$$j = \begin{cases} \text{argmax}\left\{\tau_{ij}^{\alpha}(t)\cdot\eta_{ij}^{\beta}(t)\right\}, j \in \text{allowed}_k \\ J, else \end{cases} \tag{6}$$

q is assumed to a random variable and $q \in [0,1]$; q_0 is an adjustable parameter and $q_0 \in [0,1]$. After ants complete one complete path selection cycle through n moments, the pheromone on each path will change accordingly, as seen in Equations (7) and (8).

$$\tau_{ij}(t = n) = \rho\cdot\tau_{ij}(t) + \Delta\tau_{ij} \tag{7}$$

$$\Delta\tau_{ij}(t) = \sum_{k=1}^{m}\Delta\tau_{ij}^k \tag{8}$$

where $\Delta\tau_{ij}^k$ is the pheromone of ant k on patrol nodes i and j in the current cycle; $\Delta\tau_{ij}(t)$ means the increment of pheromones of ant k on patrol nodes i and j in the current cycle. The selection model for the pheromone increment is exhibited in Equation (9).

$$\Delta\tau_{ij}^k = \begin{cases} \dfrac{Q}{d_{ij}}, If\ the\ kth\ ant\ passes\ through\ the\ path\ (i, j) \\ 0\ , miscellaneous \end{cases} \tag{9}$$

where Q is a constant.

Patrol path constraint of ACO algorithm

The patrol points on the multi-UAV task allocation and patrol path on the agricultural patrol scene are namely the paths passed during the whole patrol process and each hover photographing point, and all UAVs need to keep an enough safe distance with patrol points. Since patrol begins until ending, the hover photographing points passed by UAVs are denoted by spatial sequence points $\{O, G_1, G_2, \cdots, G_n, D\}$. O is the starting point, D is the endpoint, and $G_1, G_2, \cdots, G_n$ are the hover photographing patrol points within 3D grids during the patrol process. The connection diagram of patrol points on each path are displayed in Fig. 1.

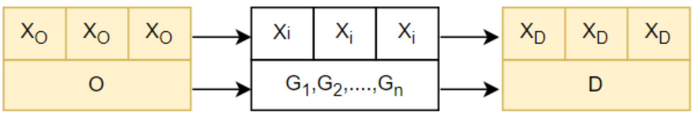

Fig. 1 - Connection diagram of patrol points on each path

In order to transform the safety requirements of patrol paths into constraints that can be used to improve ACO algorithm, UAV patrol path planning was simplified from a 3D problem into a path optimization problem within the 2D plane *(Zhu et al., 2022)*. In the process of multi-UAV task allocation and patrol path planning specific to the agricultural patrol scene, numerous constraints, such as IAVs' cruising ability and endurance and the safe distance of patrol paths and topographical conditions, should be considered. First, the minimum patrol energy consumption and the maximum patrol distance were determined as the comprehensive indexes in multi-UAV task allocation and patrol path planning facing the agricultural patrol scene, and the integral operation was performed for the comprehensive indexes on the patrol path to obtain the comprehensive index function as seen in Equation (10).

$$\begin{cases} F = \int_0^L [\lambda\omega_f + \gamma\omega_t]dt \\ \lambda + \gamma = 1 \end{cases} \tag{10}$$

where F is the comprehensive index function; L represents the patrol distance during the patrol process of UAVs; ω_f and ω_t are the minimum energy consumption constraint and the maximum patrol distance constraint, respectively; λ and γ represent the weight coefficients corresponding to the minimum energy consumption constraint and the maximum patrol distance constraint, respectively.

During the whole path optimization process, the edge combination of patrol paths can be obtained after determining the position of each spatial sequence point. Therefore, the comprehensive index function F_i of the i-th path can be obtained as per F.

$$\begin{cases} F_i = \lambda\omega_{fi} + \gamma\omega_{ti} \\ \lambda + \gamma = 1 \end{cases} \tag{11}$$

where ω_{fi} is the minimum energy consumption constraint of the i-th path; ω_{ti} is the maximum patrol distance constraint.

(1) Calculation method for energy consumption. The energy consumption of UAVs during patrol is directly proportional to the flight distance of patrol work, as seen in Equation (12).

$$\begin{cases} \omega_f = \varepsilon \times L \\ \omega_{fi} = \varepsilon \times L_i \end{cases} \tag{12}$$

(2) Maximum patrol distance. When the maximum cruising ability of UAVs is $V_{\max}$, the maximum patrol distance is displayed in Equation (13).

$$V \leqslant V_{\max}, V = \sum_{i=1}^{n-1} v_i \tag{13}$$

where V is the flight distance of spatial sequence points passed during multi-UAV task allocation and patrol process on the agricultural patrol scene; v_i is the flight distance on the i-th cruising path.

RESULTS

Simulation experiment

In this study, a total of 105 patrol points during agricultural UAV patrol process were assumed and their positions are expressed by their coordinate values X and Y, as shown in Fig. 2. The patrol speed of agricultural UAVs and the coordinates of 105 detection points are already known.

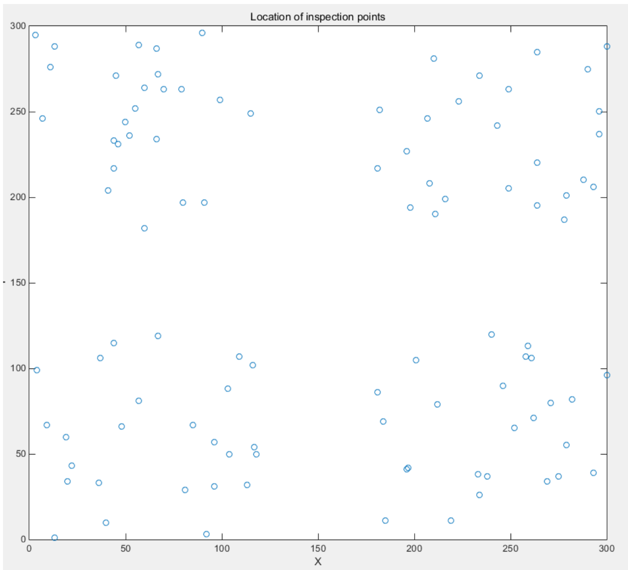

Fig. 2 - Layout plan for patrol points of agricultural UAVs

In this study, the experiment was implemented via Matlab2018a of Intel i7 processor. The multi-UAV task allocation and path planning model facing the agricultural patrol scene was solved through the improved ACO algorithm. During the simulation experiment, 100 patrol points were arranged, and the maximum patrol distance and endurance of UAVs were 120 km and 60 min, respectively. Other parameters were set to α=1.5, β=2, ρ=0.1 and Q=106. When the maximum number of iterations was Ncmax=2500 and the number of ants was m=30, agricultural UAVs must park at all monitoring points during patrol. A simulation test was performed respectively using the improved ACO algorithm and the traditional ACO algorithm, and the corresponding calculation results were compared.

Result analysis

In order to eliminate the influence of various random factors and verify the advantages and disadvantages of the improved ACO algorithm designed in this study, the improved ACO algorithm was used to solve the problem of multi-UAV task allocation and patrol path optimization specific to the agricultural patrol scene for 2500 times. The convergence curve of the improved ACO algorithm is shown in Fig. 3, and the optimal travel path of multi-UAV patrol under this scene is shown in Fig. 4.

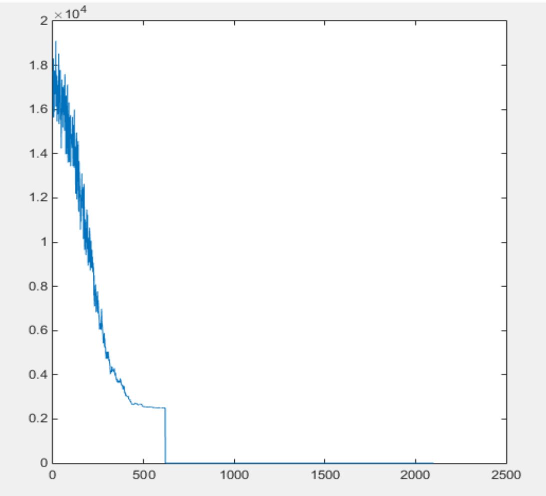

Fig. 3 - Convergence curve of improved ACO algorithm

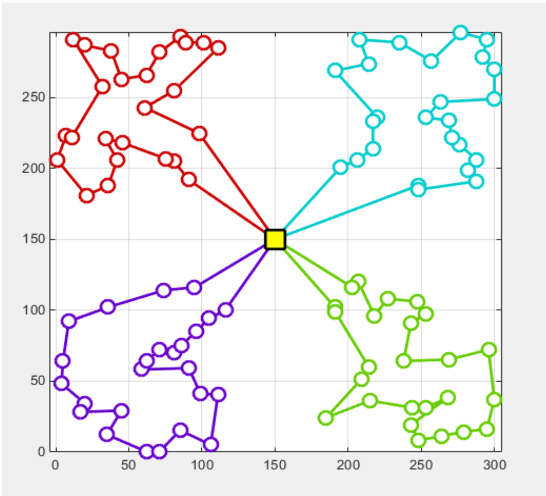

Fig. 4 - Optimal driving path of agricultural patrol UAVs

In order to verify the effectiveness of the model and algorithm, the optimization model established in this study was solved using the traditional ACO algorithm with the same parameters on the same platform. To achieve more scientific and effective experimental results, the maximum number of iterations of the traditional ACO algorithm was also set to 2500. The convergence curve of the traditional ACO algorithm is displayed in Figure 5, and the optimal multi-UAV patrol path on the agricultural patrol scene is exhibited in Fig. 6.

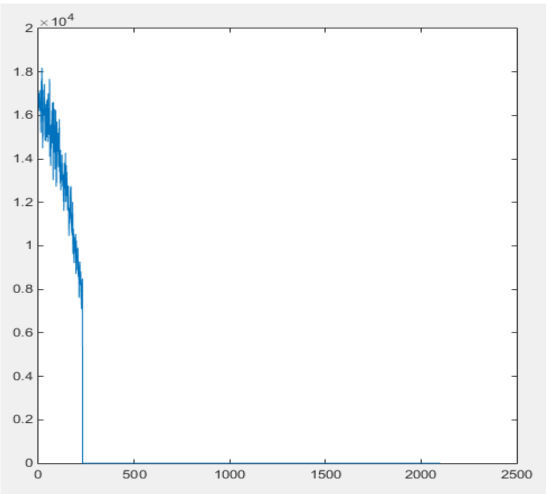

Fig. 5 - Convergence curve of traditional ACO algorithm

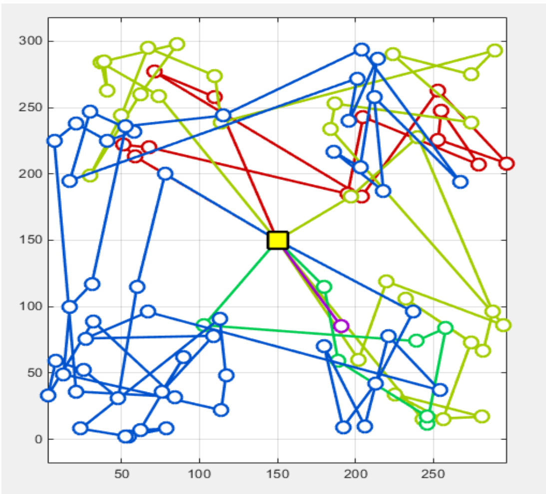

Fig. 6 - Optimal driving path of agricultural patrol UAVs

The improved ACO algorithm was compared with the traditional ACO algorithm in the patrol path and total driving distance of agricultural patrol UAVs as well as the algorithm convergence time. In comparison with the traditional ACO algorithm, the improved ACO algorithm embedded with the niche genetic algorithm showed strong exploratory and convergent properties, accompanied by the better value of the objective function. The comparison between the two algorithms is as seen in Table 1.

Table 1

Comparison between two algorithms

Algorithm	Number of UAVs	Driving distance (m)	Total cost (yuan)	Algorithm time consumption (s)
Improved ACO algorithm	4	19327.291	452.031	440.81
Traditional ACO algorithm	5	24732.394	500.799	575.48

The servo motor power of agricultural patrol UAVs was about 2200 W, and the total power of other equipment was about 80 W. Agricultural patrol UAVs needed to stop at each parking point and rotate the cloud platform for detection. The average residence time at each detection point was about 4 s, and the average drive speed of patrol UAVs was about 1 m/s. Each patrol UAV was equipped with a 50 Ah lithium battery pack, for which a 200 W AC charger was adopted. After completing inspection each time, the agricultural patrol UAV needed to return to the charging room for charging, followed by the next inspection. Therefore, the total time spent in each inspection included two parts: task time and charging time. It could be known from Table 1 that the improved ACO algorithm embedded with the niche genetic algorithm performed better than the traditional ACO algorithm in the number of UAVs, driving distance, total cost and algorithm time consumption. The traditional ACO algorithm needed 5 UAVs to put agricultural product orders in and manage warehouse output, while only 4 ones were needed by the improved ACO algorithm embedded with the niche genetic algorithm to complete the same task, improving the efficiency by 20%; in the aspect of driving distance of UAVs, the total driving distance of the traditional ACO algorithm for agricultural UAVs was 24732.394 m, while the total driving distance of the improved ACO algorithm embedded with the niche genetic algorithm for completing the same task was 19327.291 m, and the path was shortened by 27.96%; the total cost spent by the traditional ACO algorithm in agricultural UAVs was 500.799 yuan, while that for the improved ACO algorithm embedded with the niche genetic algorithm to complete the same task was 452.031 yuan, saving the cost by about 10.79%; in terms of algorithm time consumption, it took 575.48 s for the traditional ACO algorithm to converge, while the convergence time for the improved ACO algorithm embedded with the niche genetic algorithm was 440.81 s, with the algorithm efficiency improved by 30.55%. It could be seen from Table 1 that the improved ACO algorithm showed stronger optimization ability and convergence than the traditional ACO algorithm. As intuitively observed from the algorithm convergence curves, the optimal path length acquired by the improved ACO algorithm was better than that of the traditional ACO algorithm when it comes to the total patrol distance of agricultural UAVs.

CONCLUSIONS

In this study, the multi-UAV task allocation problem facing the agricultural patrol scene was summarized, and the existing relevant work was reviewed. Specifically, a distributed task allocation and path planning algorithm was put forward aiming at the task allocation and path planning algorithm on the agricultural patrol scene. This method fully considered the coupling of task allocation with path planning in the process of task allocation, thus ensuring that the patrol task allocated to UAVs conformed to reality more. Besides, the maximum endurance constraint of UAVs was considered. The experiment manifested that when UAVs executed the patrol task, the improved ACO algorithm embedded with the niche genetic algorithm in this study had a total cruising range nearly 5405.103 m shorter than that obtained by the current advanced algorithms. In comparison with the traditional ACO algorithm, the proposed algorithm improved the convergence efficiency by 30.55%. In a word, the effectiveness and practicability of embedding the niche genetic algorithm were experimentally verified. Relevant research not only proves that Tent optimization ant colony algorithm has a good application in UAV inspection path optimization, enriching the practical application value of the algorithm, but also provides a reference for the theoretical research of related algorithms. However, a faster global path planning algorithm is not considered in this study for the time being, and the proposed algorithm will be further verified in real application scenarios deployed in the future.

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