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Multi-UAV Cooperative Path Planning with Monitoring Privacy Preservation

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Abstract: UAVs have shown great potential application in persistent monitoring, but still have problems such as difficulty in ensuring monitoring frequency and easy leakage of monitoring path information. Therefore, under the premise of covering all monitoring targets by UAVs, it is necessary to improve the monitoring frequency of the target and the privacy protection of the monitoring intention as much as possible. In response to the above problems, this research proposes monitoring overdue time to evaluate the monitoring frequency and monitoring period entropy in order to evaluate the ability to ensure monitoring privacy protection. It then establishes a multi-UAV cooperative persistent monitoring path planning model. In addition, the multi-group ant colony optimization algorithm, called overdue-aware multiple ant colony optimization (OMACO), is improved based on the monitoring overdue time. Finally, an optimal flight path for multi-UAV monitoring with high monitoring frequency and strong privacy preservation of monitoring intention is obtained. The simulation results show that the method proposed in this paper can effectively improve the monitoring frequency of each monitoring node and the privacy preservation of the UAV monitoring path and has great significance for enhancing security monitoring and preventing intrusion.

Keywords: persistent monitoring; privacy protection; path planning; monitoring frequency; overdue time

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1. Introduction

For the purposes of public safety, environmental protection, scientific research, etc., people need to observe, measure and collect information in certain areas over a long time, and then make decisions based on the results of these observations, measurements and collection. This is generally called a persistent monitoring problem [1–3]. Monitoring in person or by hand is usually constrained by weather, geography, working hours and labor costs, and intelligent equipment can greatly overcome the above deficiencies of human based monitoring. Unmanned aerial vehicles (UAV) are examples of one of these typical intelligent monitoring devices. Because they are free of human intervention and offer stable flight, a wide range of motion, and low cost, UAVs are often used to perform persistent monitoring tasks [4], target detection and tracking [5], and border patrols [6]. This research mainly studies the UAV path planning problem when they are used in persistent monitoring.

With the emergence of various complex environments and complex tasks, a single UAV will find it hard to meet the requirements of increasingly complex inspection operations. Consequently, there has been extensive research on multi-UAV cooperation. Compared with single-UAV operation, multi-UAV cooperation has demonstrated greater advantages. For example, multi-UAV cooperation [7,8] can obtain more comprehensive and wide information and can realize multi-angle monitoring of the target area. However, such problems as cooperation strategy, inconsistent monitoring frequency, unsynchronized monitoring information, and unsafe monitoring strategies still exists for multi-UAV cooperation. The task decisions of multi-UAV persistent monitoring have become popular issues in the application field of UAVs.

The multi-UAV persistent monitoring problem can be divided into two levels. One level is the monitoring frequency constraint, and the other is the persistent monitoring security, i.e., monitoring privacy preservation. The above two levels correspond to the two so-called modes of UAV persistent monitoring. One is the regular monitoring mode, that is, the route planned for the UAV to minimize the time delay between each adjacent visit of the task nodes and to improve their monitor frequency as much as possible. The other is the adversarial monitoring mode, which is to plan uncertain, unpredictable and non-periodic monitoring paths for UAVs in order to prevent any intelligent intruders from detecting the monitoring regularity [9]. If the monitoring frequency constraint is considered as the only criterion, the monitoring path is usually a certain periodic path. Once an intelligent intrusion appears in the monitoring environment, the privacy of the UAV monitoring intention cannot be protected, and the monitoring task is easily destroyed by intelligent intruders. On the other hand, when only the security of persistent monitoring is considered, it may be difficult to satisfy the monitoring frequency requirements of each node due to excessive consideration of path privacy security. Therefore, it is of great theoretical significance and practical value to study the joint optimization problem of monitoring frequency and privacy protection.

Portugal [10] reviewed the multi-robot cooperative patrol algorithms that has been studied in recent years and pointed out that a distributed, non-deterministic and cooperative strategy represents the future trend. Alamdari [11] studied the persistent monitoring problem of a single robot. The optimization goal is to minimize the revisit duration of the given monitoring tasks. Two approximate algorithms with complexity $O(\log \rho_G)$ and $O(\log n)$ were proposed, respectively. Elmaliach [12] studied the patrol problem in a closed area and proposed the patrol frequency optimization criterion for the first time, and each point in the area should be repeatedly visited by multiple robots. Smith [3,13] studied persistent monitoring problems in discrete and continuous environments, and established two optimization models, aiming to enhance the monitoring frequency. Wang [14] studied the persistent monitoring problem of multiple UAVs and established a mathematic model based on the optimization of the maximum environmental recognition accuracy, which was then solved by a heuristic algorithm. Kalyanam [15] studied a similar problem, i.e., UAV data collection, allowing UAVs to visit some targeted location with high priority more than once in a single cycle. An optimization by maximizing the average period reward was formulated, and the precise solution combining dynamic programming and mixed integer linear programming was achieved. Subsequently, considering the scalability of the algorithm and improving its efficiency, an approximate solution was proposed for the nodes with specific visiting times [16]. Von [17] also discussed the algorithm scalability where a genetic algorithm was used to obtain the approximate solution that showed better scalability than a precise method through experiments. Scherer [18] studied a multi-UAV cooperative path planning problem with monitoring data transport for the purpose of minimizing the time delay between data being captured by UAVs and the arrival of the data at the base station. Hari [19] considered the monitoring frequency constraint and set the fixed horizon to a given number, k, which assumes that the UAV can only access k nodes in each cycle. However, once there exists an intelligent intrusion in the monitoring environment, the monitoring privacy will have already been destroyed. The above persistent monitoring studies considered monitoring frequency constraints, but only focused on the monitoring performance or coverage rate of the given area [20] and did not consider monitoring security issues in an adversarial environment.

With regard to the concern for monitoring security, one also needs to consider how easy the monitoring strategy can be acquired by intelligent intruders. The privacy of the persistent monitoring process is of great concern, especially in some applications where intelligent adversaries or intruders might occur. At present, there are at least two ideas in the field of monitoring security. One is to improve the existing deterministic strategy for the path planning problem and use random algorithms instead, such as Markov chains, or random walk theory. The other is to establish a game model and a balance scheme between the competing players. Agmon [21] proposed a Markov strategy, which is a polynomial-time algorithm, and their research is motivated by reducing the probability of being invaded at a weak task position as much as possible. Entropy has also been introduced in path planning [22]. For example, George [23] and Duan [24] studied the entropy rate maximization problem based on Markov chains. Stackelberg game theory was used by Basilico [25] to formulate an optimal solution to the path planning problem for a single robot on a security patrol, while assuming only one intruder. Security game theory has been proposed for the study of the persistent monitoring path planning problem in ecological protection [26]. The main motivation for their study on patrol and monitoring strategies is to obtain an unpredictable trajectory, which was finally obtained through maximum entropy.

With the aforementioned observations, some studies on persistent monitoring path planning only concern the complete coverage rate, and some studies consider the monitoring frequency, but the final paths often fall in a fixed monitoring period which makes the monitoring regularity completely exposed to intrusions. The other study considers monitoring security, but they still do not consider monitoring frequency constraints. To bridge the gap between the monitoring frequency and monitoring security, this study will comprehensively consider both sides simultaneously, that is, improving monitoring path privacy while increasing monitoring frequency. The main contributions of this paper are as follows:

- Considering monitoring frequency and path privacy, this study shows how to formulate a multi-UAV cooperative persistent monitoring path planning problem with multiple constraints based on the monitoring of overdue time and of monitoring period entropy.
- A multi-group ant colony optimization algorithm, called overdue-aware multiple ant colony optimization (OMACO), is proposed to obtain an optimal flight path for UAV cooperation. The heuristic function and pheromone update method are improved based on the monitoring delay time and overdue time. In addition, a target exclusive mechanism and greedy strategy are proposed for ant node selection.
- Simulation experiments are carried out in complete and incomplete environments to verify the effectiveness and advantages of the designed algorithm. The simulation results show that the algorithm proposed in this paper can effectively improve both the monitoring frequency and the monitoring privacy protection.

2. Multi-UAV Cooperative Persistent Monitoring Path Planning Model

2.1. Problem Description

As the monitoring environment changes and the node quantity increases, computer resources onboard are often insufficient when performing persistent monitoring tasks in the stand-alone operation mode. As a result, the waiting time of nodes increase, causing some nodes to monitor overdue. Compared with a single drone, a drone group performing persistent monitoring tasks will face huge challenges. For example, each node will maintain a parameter that represents how long it has been waiting since its last monitoring. Once any drone visits a node position and completes that monitoring, the waiting-time parameter maintained by this node will be cleared— demonstrating a rigid nonlinearity. Other difficulties include collision avoidance between multiple drones, information synchronization, and collaborative work between drones.

This study focuses only on the multi-UAV cooperative path planning problem of persistent monitoring. A graph model is used to describe the distribution of the candidate nodes, i.e., $G = (V, E)$, where $V = \{1, 2, \ldots, N\}$ represents the nodes set, N represents the total number of nodes, and $E = \left\{e_{ij}, \forall i, j \in V\right\}$ represents the edges set of G. The UAV set is $M_{UAV} = \{1, 2, \ldots, M\}$, where M is the total number in the given UAV group, $M << N$. Here are some assumptions about the background of this study.

(1) For safety and efficiency purposes, the same nodes cannot exist for multiple drones at the same time. This means that different UAV are permitted to monitor the same node on different time.

(2) Without loss of generality, all UAVs fly with a constant speed, v.

(3) After a UAV accesses a node, the waiting time of the node is cleared, and all other UAVs need to be notified to ensure information synchronization.

This research tries to find the optimal flight path of a UAV group, so that the path meets the requirements of high monitoring frequency and strong monitoring path privacy.

2.2. Discretization of the Graph

Persistent monitoring needs to consider UAV movement synchronization. In order to solve the problem, a discrete approximation operation is introduced on the graph G. Several virtual nodes are inserted in an approximately uniform way to the edges of G leading to a discretized graph that includes many more edges of equal intervals, denoted by δ. This operation encourages good behavior in which any UAV will certainly move forward from its current node position to its neighbor node in G instead of staying between nodes at time step k. This is called UAV movement synchronization. Consequently, nodes can be divided into two categories, one is the **task node** set, V, which requires monitoring and the other is the **virtual node** set, U, which is generated during discrete approximation operation and does not to be monitored. The complete node set, called a **generalized node** set, is denoted as $V' = V \cup U = \{1, 2, \ldots, N + |U|\}$. It should be emphasized that all virtual nodes in U are not real monitoring tasks, so they do not need to record their monitoring delays. The final adjacency matrix of G is $A \in \mathbb{R}^{(N+|U|)\times(N+|U|)}$, where any element a_{ij} is binary. $a_{ij} = 1$ indicates that node i and j are adjacent to each other, otherwise $a_{ij} = 0$.

2.3. Multi-UAV Collaborative Monitoring Constraints

Let K denote the maximum length of the monitoring horizon. Let the binary variable matrix $Y^m \in \mathbb{R}^{K\times(N+|U|)}$ denote whether a node is monitored by UAV m, $m \in M_{UAV}$. For $\forall i \in V'$, the element $y^m_{k,i} = 1$ represents that the node i is monitored by UAV m at time k, and $y^m_{k,i} = 0$ represents that the node i is not monitored by UAV m at time k. Y^m represents the monitoring of all nodes by UAV m in the entire monitoring time horizon.

Let the binary variable matrix $X \in \mathbb{R}^{K\times(N+|U|)}$ represent whether a node is monitored by any UAV in the group, where the element $x_{k,i} = 1$ represents that there is at least one UAV monitoring node i at time k, and the element $x_{k,i} = 0$ represents that node i is not monitored by any UAV at time k. The matrix X stands for the monitored situation of all nodes in the monitoring time horizon, and can be obtained by combining all Y^m, $m = 1, 2, \ldots, M$. The relationship between X and Y^m is $X = Y^1 \cup Y^2 \ldots \cup Y^M$. The constraints are as follows:

$$x_{k,i} = \begin{cases} 0, \text{if } \sum\limits_{m=1}^{M} y^m_{k.i} = 0, \\ 1, \text{otherwise, i.e., } \sum\limits_{m=1}^{M} y^m_{k.i} = 1 \end{cases} \tag{1}$$

where $i \in V, k \in \{1, 2, \ldots, K\}$

$$\sum_{m=1}^{M} y^m_{k.i} \leq 1, i \in V', k \in \{1, 2, \ldots, K\} \tag{2}$$

$$\sum_{k=1}^{K} x_{k,i} \geq 1, i \in V \tag{3}$$

$$\sum_{i=1}^{N+|U|} x_{k,i} = M, k \in \{1, 2, \ldots, K\} \tag{4}$$

Equation (2) indicates that at any time k, a node is monitored by, at most, one UAV, that is, multiple UAVs cannot appear at the same location at the same time. Equation (3) indicates that within the monitoring horizon K, each node must be visited at least once. Equation (4) indicates that a UAV only has one position at a certain time k.

2.4. UAV Motion Constraints

Assuming that the initial moment k=1, all the UAVs need to start from the same given initial node $S_m \in V$. The following constraints are satisfied:

$$y^m_{1,S_m} = 1, m \in M_{UAV} \tag{5}$$

At the same time, the UAV m cannot visit the same node in two adjacent time steps:

$$y^m_{k,i} + y^m_{k+1,i} \leq 1, i \in V, k \in \{1, 2, \ldots, K-1\}, m \in M_{UAV} \tag{6}$$

2.5. The Waiting Time Constraint of the Task Node

Let $F \in \mathbb{R}^{(K-1)\times N}$ represent the whole task nodes' waiting time, in which the element is $f_{k,i} \geq 0$. In the interval between time step k-1 to k, all UAVs select a candidate node from their individual neighbor according to a certain movement strategy. After that, the waiting time of almost all nodes increases by one unit time except the arrived node i which is exactly a task node. That is, $i \in V$. The waiting time corresponding to the arrived node i will be cleared. Therefore,

$$f_{k,i} = \begin{cases} 0\,, & i \in V, k = 1 \\ (1 - x_{k,i})(f_{k-1,i} + c), & i \in V, k \in \{2, 3, \ldots, K\} \end{cases} \tag{7}$$

where c is a unit time constant, which represents the time consumed by the UAV when passing through each edge interval. This specific value is related to the accuracy of the discretization operation.

2.6. Min–Max Optimization for Multi-UAV Cooperative Monitoring

2.6.1. UAVs Monitoring Overdue Time Evaluation

Let the maximum monitoring interval of a task node i between two adjacent monitoring events be the expected period of the node, denoted by T_i, $i \in V$. Ideally, for any time k, the waiting time of node i should not exceed its expected period. That is

$$0 \leq f_{k,i} \leq T_i, i \in V, k \in \{1, 2, \ldots, K\} \tag{8}$$

However, in practical applications, since the number of UAVs is far less than the quantity of the task nodes, it is inevitable that some nodes' monitoring will be overdue. The overdue time can be expressed as $f_{k-1,i} + c - T_i$. Define the real monitoring period of the task node as $P \in \mathbb{R}^{K\times N}$:

$$p_{k,i} = \begin{cases} 0, & i \in V, k = 1 \\ x_{k,i}(f_{k-1,i} + c), & i \in V, k \in \{2, 3, \ldots, K\} \end{cases} \tag{9}$$

The above equation indicates that when the UAV arrives at node i at time step k, i.e., $x_{k,i} = 1$, the real monitoring period of this node is $f_{k-1,i} + c$. Otherwise, $p_{k,i}$ have no definition and it will be assigned to zero. Therefore, the maximum monitoring period of the task node i in the entire monitoring horizon is:

$$\max_{k\in\{1,2,\ldots,K\}} p_{k,i} \tag{10}$$

Then, the maximum overdue time of the task node i caused by exceeding its expected period T_i can be expressed as:

$$\max\left\{0, \max_{k\in\{1,2,\ldots,K\}}(p_{k,i} - T_i)\right\} \tag{11}$$

The following objective, J_1, is proposed for optimization by minimizing the normalized maximum overdue time of all task nodes.

$$\min_{Y,F} J_1 = \max_{i\in V}\left(\frac{1}{T_i}\max\left\{0, \max_{k\in\{1,2,\ldots,K\}}(p_{k,i} - T_i)\right\}\right) \tag{12}$$

2.6.2. UAVs Monitoring Path Privacy Criterion

As long as any UAV accesses a task node, its waiting time will be cleared. Therefore, it is necessary to evaluate the privacy of the monitoring path based on the actual visiting period of all task nodes. Since the uncertainty of the monitoring period indirectly reflects the monitoring privacy, this study proposes the concept of monitoring period entropy (MPE) which refers to the uncertainty when the UAV returns to the task node for monitoring again. The larger the MPE, the higher the randomness of the monitoring period. Define a vector $\widetilde{p}_i = \{p_{k,i} | p_{k,i} > 0, k = 1,2,\ldots,K\}$ to represent the vector composed of all the monitoring cycles of task node i in the entire monitoring horizon. The length of the vector, $\widetilde{p}_i$, is $l_{\widetilde{p}_i} = \sum_{k=1}^{K} x_{k,i}$. Define the monitoring period entropy of node i as:

$$H(\widetilde{p}_i) = -\sum_{j=1}^{l_{\widetilde{p}_i}} P(\widetilde{p}_i(j)) \log P(\widetilde{p}_i(j)) \tag{13}$$

where $P(\widetilde{p}_i(j))$ is the probability that the jth element in vector $\widetilde{p}_i$. One should note that $H(\widetilde{p}_i)$ is always positive. The minimum monitoring period entropy among all task nodes is:

$$\min_{i\in V} H(\widetilde{p}_i) \tag{14}$$

Therefore, in order to improve the randomness of the monitoring period, the optimization objective is designed to maximize the entropy of the smallest monitoring period among all task nodes, namely $\max_{Y,F}\left(\min_{i\in V} H(\widetilde{p}_i)\right)$. This criterion is also equivalent to the reciprocal of the minimum monitoring period entropy (because $H(\widetilde{p}_i)$ is a positive number), so the following optimization objectives can be designed:

$$\min_{Y,F} J_2 = \frac{1}{\min_{i\in V} H(\widetilde{p}_i)} \tag{15}$$

The dimension of the multi-UAV path solution $\boldsymbol{Y}$ is $K \times (N + |U|)$, and the algorithm time complexity of the calculation for the monitoring of overdue time and the evaluation of path privacy is $O(n^2)$.

2.6.3. Multi-UAV Persistent Monitoring Path Planning Model

The optimization problem of multi-UAV cooperative persistent monitoring path planning is expressed as follows:

$$\begin{aligned} \min_{Y,F} \quad & J = wJ_1 + (1-w)J_2 \\ \text{s.t.} \quad & (1) - (8) \end{aligned} \tag{16}$$

where $w \in (0,1)$ represents the weight coefficient, which will balance between the performance of overdue time and path privacy.

3. Improved Multi-Group Ant Colony Optimization Algorithms Based on Monitoring Overdue Time

From the perspective of reducing monitoring overdue time and improving path privacy, this section designs an improved ant colony optimization (ACO) algorithm based on the monitoring of overdue time, called an overdue-aware multiple ant colony optimization algorithm. Major improvements include the aspects:

- A greedy strategy for node selection is proposed, in which the ant colony heuristic function is modified using the expected period of the task nodes.
- Ant colony pheromone is updated based on monitoring overdue time and monitoring period entropy.
- A target exclusion mechanism is proposed to improve the utilization rate of multi-UAV in cooperative monitoring.

3.1. Heuristic Function Based on Monitoring Expectation Period

In order to increase the monitoring frequency and reduce the visiting delay of each task node, the improved heuristic function, η_{ij}, is as follows:

$$\eta_{ij} = \frac{1}{T_j d_{ij}} \tag{17}$$

where d_{ij} represents the distance between node i and j. Comparing with the traditional heuristic function in ACO, Equation (17) takes into account the expected period (T_j) of the neighbor task nodes, which is helpful in reducing its monitoring overdue time.

3.2. Target Exclusion Mechanism

When multiple UAVs perform tasks at the same time and do not consider the path privacy issue, multiple UAVs will be evenly distributed on the minimum Hamiltonian cycle of the graph [25]. The ants select generalized nodes (task nodes or virtual nodes are both possible) depending on stochastic probability. Therefore, there is a slim chance that the UAV follows its previous UAV when selecting its next node, which results in some nodes being monitored frequently while other task nodes are missed for a long time. Consequently, monitoring overdue events happen. In order to prevent UAVs from following synchronically, this research proposes a target exclusion mechanism, as shown in Figure 1.

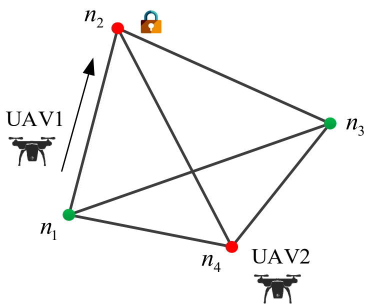

Figure 1. Target exclusion mechanism.

As an example, when UAV1 in Figure 1 selects node n_2 as the candidate task node, UAV1 exclusively occupies node n_2 and the node n_2 will be locked. However, UAV2, which is currently located at node n_4, cannot select the locked node as its candidate. Only one of n_1 and n_3 will be chosen as the UAV1's next waypoint. The target exclusive mechanism can fundamentally solve the UAV following problem.

3.3. Greedy Strategy for Node Selection

This section proposes a greedy strategy, which can help UAV select the optimal node among its neighbors. The strategy is motivated by the idea that the greater the overdue time of the ant's adjacent node j is, the greater the probability that node j will be selected by the ants in the next step. First calculate the overdue time of all adjacent nodes. Since some adjacent nodes may not be overdue, the calculated overdue time by $f_{k-1,j} + c - T_j$ is possibly negative and inconvenient to compute the transition probability. Therefore, this research constructs a pseudo-overdue time, $R_j(t)$, which is guaranteed to be positive.

$$R_j(t) = f_{k-1,j} + c - T_j + T_0, \forall k \in P \tag{18}$$

where j represents the adjacent node of the current node. T_0 represents the upper bound of the expected period of all monitoring nodes. Usually, it can be calculated by $T_0 = \max_{i \in V}\{T_i\}$ offline.

The transition probability is not only related to the overdue time of its neighbor node, but also related to the adjacency constraints, exclusive flags, and pheromone distribution of the ants' current adjacent nodes. The improved ant transition probability p_{ij}^z is as follows:

$$p_{ij}^z = \begin{cases} \dfrac{\tau_{ij}^{\alpha}(t)\eta_{ij}^{\beta}(t)R_j(t)a_{ij}(1-o_j)}{\sum\limits_{s \in allow_z} \tau_{is}^{\alpha}(t)\eta_{is}^{\beta}(t)R_s(t)a_{is}(1-o_s)}, & j \in allow_z \\ 0\,, & \text{other} \end{cases} \tag{19}$$

where i is the current node of the ant whose adjacent node is denoted by j. α and β stand for the importance factor of the pheromone and the heuristic function, respectively, $\tau_{ij}(t)$ represents the pheromone concentration on the edge e_{ij} after the optimization of each ant at the t-th iteration. a_{ij} stands for the adjacency relationship between node i and j, o_j represents the exclusive state of the node j, $z \in \{1, 2, 3, \ldots, Z\}$ represents the ant number, z is the ant quantity, and $allow_z$ represents the set of nodes that the ant z can visit next time. After the transition probability of the ants is calculated, the roulette method is used to select the next node according to the maximum probability.

3.4. Pheromone Update Based on Monitoring Overdue Time and Monitoring Period Entropy

The traditional ant colony algorithm updates the pheromone mainly based on the path length that ants travelled. In order to promote the evolution of the ant colony to the direction with the smallest cost function value, this study updates the pheromone according to the optimization objective (16).

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \sum_{z=1}^{Z} \Delta\tau_{ij}^z \tag{20}$$

$$\Delta\tau_{ij}^z = \begin{cases} \frac{Q}{J_z}, \text{ant } z \text{ from node } i \text{ to node } j \\ 0\,, \text{other} \end{cases} \tag{21}$$

where $\rho \in (0,1)$ represents the pheromone volatile factor. $\Delta\tau_{ij}^z$ represents the pheromone concentration released by the ant z on the edge between node i and j in the current iteration. Q is a constant, representing the total pheromone amount released by the ants at one time, and J_z represents the path cost of the ant z calculated according to (16).

To sum up, the scheme of the proposed OMACO algorithm is shown in Figure 2. The steps are as follows in Algorithm 1:

Algorithm 1: Overdue-aware multiple ant colony optimization (OMACO).

Step 1: Initialization (node quantity N, adjacency matrix A, ant quantity Z, maximum iterations N_c, pheromone importance factor α, heuristic function importance factor β, pheromone volatility factor ρ, pheromone quantity Q, and maximum monitoring horizon K, weight parameter w).
Step 2: Discretization of the graph.
Step 3: Calculate the target exclusion set O_0.
Step 4: Calculate the ant transition probability p_{ij}^{z} according to (19).
Step 5: Select the next node according to the roulette method, and update the node waiting time $f_{k,i}$.
Step 6: Update the ant's taboo table.
Step 7: Update the target exclusive flag o_i.
Step 8: Calculate the monitoring overdue time and monitoring period entropy according to (11) and (13).
Step 9: Update pheromone according to (20) and (21).
Step 10: Determine whether the iteration reaches the maximum iterations. If so, the procedure ends; otherwise, go to Step 3.

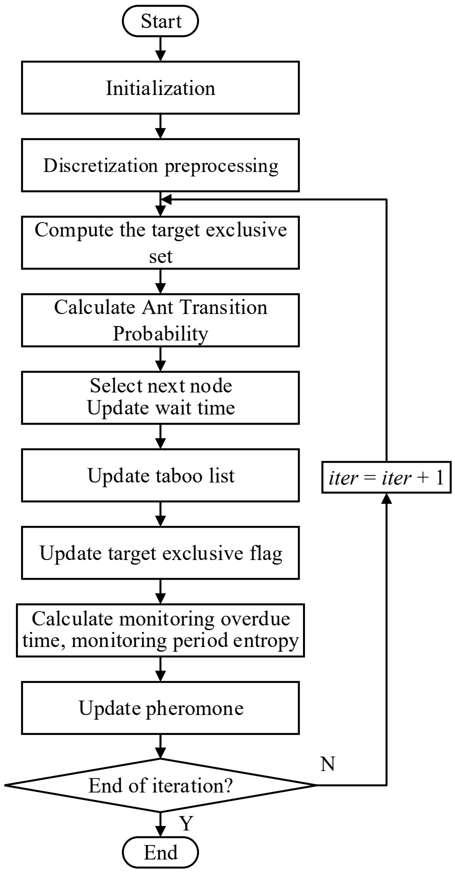

Figure 2. Flowchart of the OMACO algorithm.

4. Simulation Experiments and Discussions

In this section, simulation experiments are carried out for multi-UAV persistent monitoring tasks in complete and incomplete environments to evaluate the path planning model and solution algorithm proposed in this study.

4.1. Algorithm Feasibility Analysis

Assume that three UAVs perform tasks in a complete environment containing 10 task nodes with known locations to be monitored, which are labeled as numbers in Figure 3. Task nodes and virtual nodes are illustrated by red and green dots, respectively. The blue solid lines represent adjacency relationships within the graph. All the simulation parameters are listed in Table 1. The expected periods of the task nodes are shown in Table 2. All simulation examples in this paper are implemented on a computer with Matlab R2020a installed and the system configuration is Intel Core i7-9750H, 2.59 GHz, 16 GB RAM.

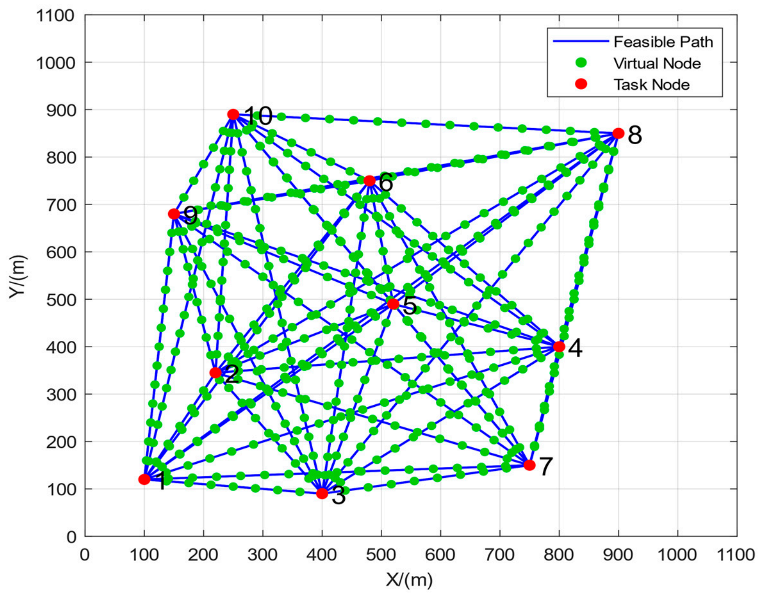

Figure 3. Discretization of a completely connected graph.

Table 1. Simulation parameters.

Parameters	Value	Notes
v	8 m/s	UAV speed
δ	40 m	interval for discretization
Z	15	ant quantity
c	5 s	constant
N_c	200	maximum iteration
α	1.2	pheromone importance factor
β	4	heuristic function importance factor
ρ	0.3	pheromone volatility factor
Q	10	pheromone quantity
K	500	monitoring Horizon
w	0.6	weight parameter

Table 2. Expected period of 10 task nodes.

Node	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
T_i **(s)**	370	380	350	375	365	390	380	380	375	360

Figure 4 shows the persistent monitoring flight path of the three UAVs obtained by the proposed method in this paper, where the x-axis represents the time, and the y-axis represents the node that the UAV arrived at the corresponding time step. The solid line represents the UAV flight path consisting of passing nodes.

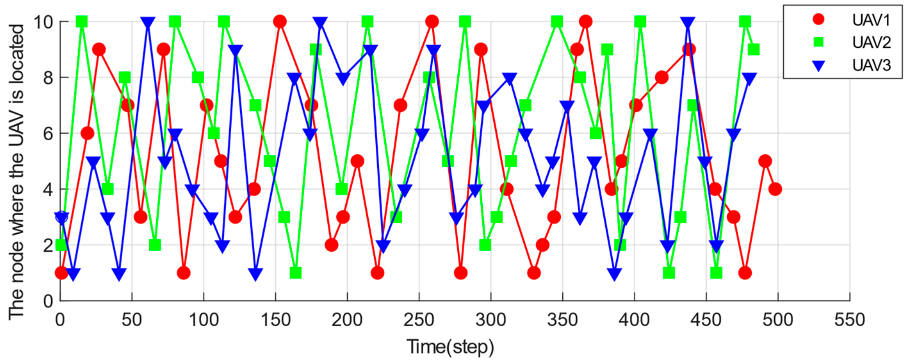

Figure 4. The persistent monitoring path obtained by the OMACO algorithm.

Figure 5 shows the expected period and the actual monitoring period of the task nodes. It can be seen that the actual monitoring period of all task nodes is less than the expected period, which indicates that the monitoring process of the UAV meets the monitoring frequency requirements of all nodes. Figure 5 also shows that each node has been visited multiple times in the monitoring horizon, obtaining multiple actual monitoring periods which are all lower than their expected periods, i.e., meeting the monitoring frequency requirements.

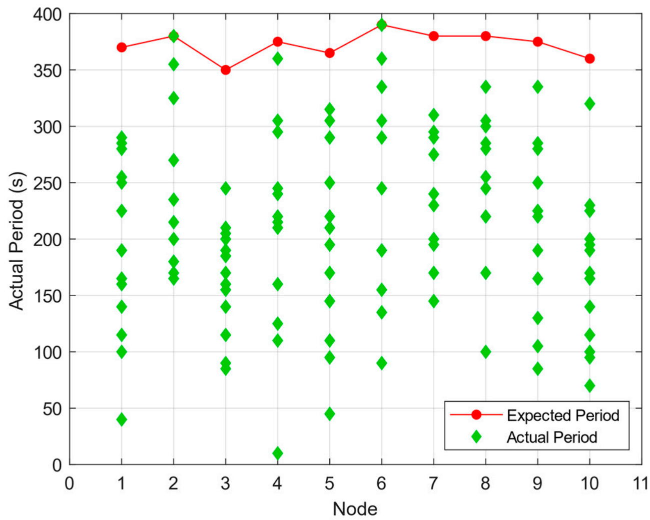

Figure 5. The actual monitoring period of task nodes obtained by the OMACO algorithm.

More importantly, the actual monitoring period of each node is different, that is, the waiting time when each node is monitored has a good random distribution. The simulation shows that the method proposed in this paper can cover all monitoring nodes, meet the monitoring frequency requirements, and also improve the privacy protection of the monitoring path.

4.2. Comparative Analysis with Traditional ACO

In order to evaluate the performance of the proposed OMACO algorithm, this section compares the optimization ability of OMACO and the traditional ACO. Figure 6 shows the monitoring path solved by the traditional ACO with the same parameters to Section 3.1. Different from Figure 4, the path sequences (node 6 $\rightarrow$ 7 $\rightarrow$ 9) repeat up to eight times in Figure 6, and the UAV3 trajectory (blue) between steps 450 and 500 can be seen following by UAV1 (red). This leads to the same monitoring period and is very harmful to the monitoring privacy protection. However, the UAV path in Figure 4 has no obvious repetitive path or circular trajectory, and there is no UAV following the other. Therefore, compared with the traditional ACO, the proposed OMACO algorithm can obtain better privacy protection performance.

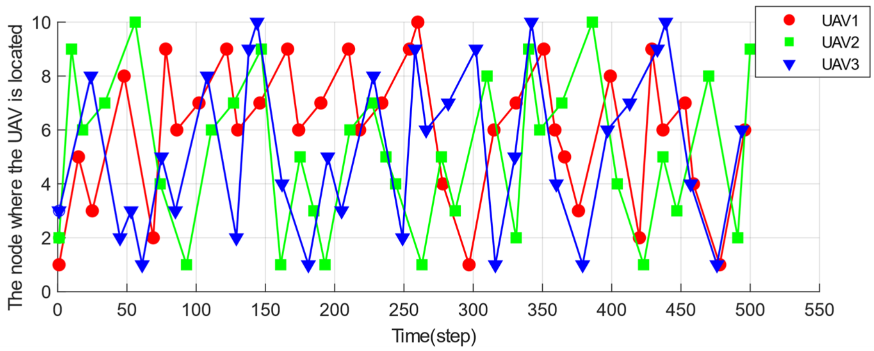

Figure 6. The persistent monitoring path obtained by ACO algorithm.

Figure 7 shows the actual monitoring period obtained by using the traditional ACO. There exist many nodes that have been monitored overdue many times, resulting in the waiting time of the task node frequently exceeding the expected period. Therefore, the proposed OMACO algorithm is superior to the traditional ACO in improving the monitoring frequency.

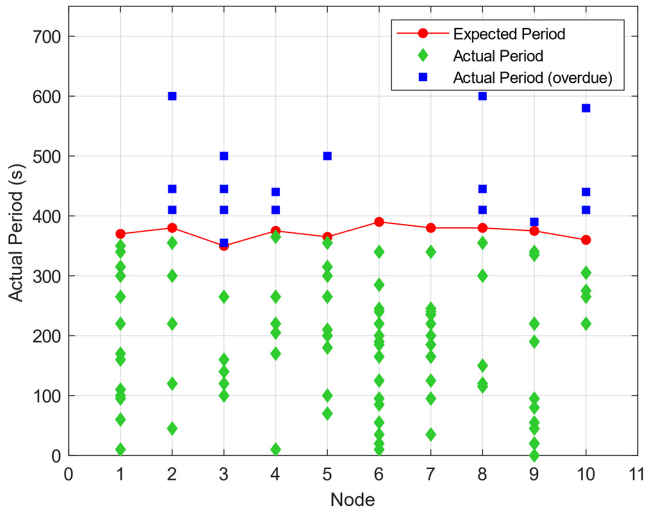

Figure 7. The actual monitoring period of each node obtained by ACO algorithm.

Table 3 shows a detailed comparison between OMACO and ACO on each task node monitoring data. Based on the proposed OMACO algorithm, most task nodes have been visited more times than that of ACO. Therefore, the average visit number is higher than the traditional ACO. Correspondingly, the average actual period will decrease and be less than ACO. Also, it is found that the ACO algorithm is not appropriate for our problem because the node No.10 exceeds its upper bound.

Figure 8 shows the iterative curves of the objective functions obtained by OMACO and ACO, and the related data are shown in Table 4. In the first iteration, the algorithm designed in this research has a lower value of objective function than ACO. This is because the waiting time of the task node has already been considered by OMACO when calculating the transition probability based on the greedy strategy. In fact, the node selection strategy has been optimized before the initial ant path. The traditional ACO only relies on the heuristic function and pheromone to decide the node transition probability. Consequently, the pheromone is equal on all path segments in the initial iteration which leads to a randomly path generated.

Table 3. Monitoring results comparison between OMACO and ACO.

Node	Number of Visits		Average of Actual Monitoring Period	
	OMACO	ACO	OMACO	ACO
1	12	12	198.33	198.75
2	9	7	253.33	350.00
3	14	8	167.14	278.75
4	11	8	232.50	286.25
5	12	9	204.17	242.22
6	9	15	260.00	165.00
7	10	12	220.00	188.33
8	9	7	266.11	335.00
9	11	15	219.09	166.33
10	14	6	170.00	365.00 *
Average	11.1	9.9	219.07	257.56

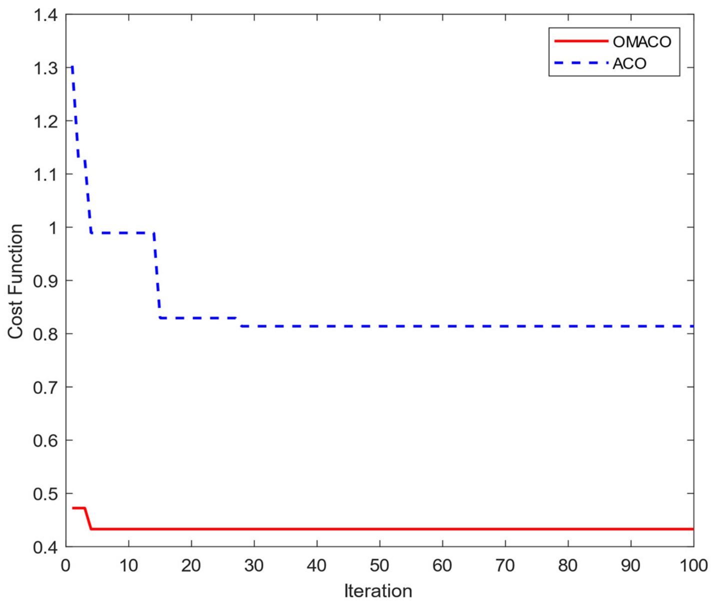

Figure 8. The objective function iteration curves of the two algorithms.

Table 4. Solution comparison between OMACO and ACO.

	OMACO	ACO
Iterations	4	28
Minimum Cost	0.433	0.814

The OMACO algorithm gets the optimal solution of 0.433 in the 4th iteration while the traditional ACO only obtains the optimal solution of 0.814 in the 28th iteration. Since the OMACO algorithm introduces the overdue time for optimization, it is significantly better than the ACO in terms of reducing the monitoring overdue time and improving the monitoring path privacy.

4.3. Algorithm Scalability Analysis

This section demonstrates the simulation experiments with three UAVs performing persistent monitoring in an incomplete environment which contains 15 task nodes. Other parameter settings are the same as in Section 3.1. Figure 9 shows the environment topology where 15 task nodes connected incompletely will be persistently monitored by the UAVs. The expected period of 15 nodes is shown in Table 5.

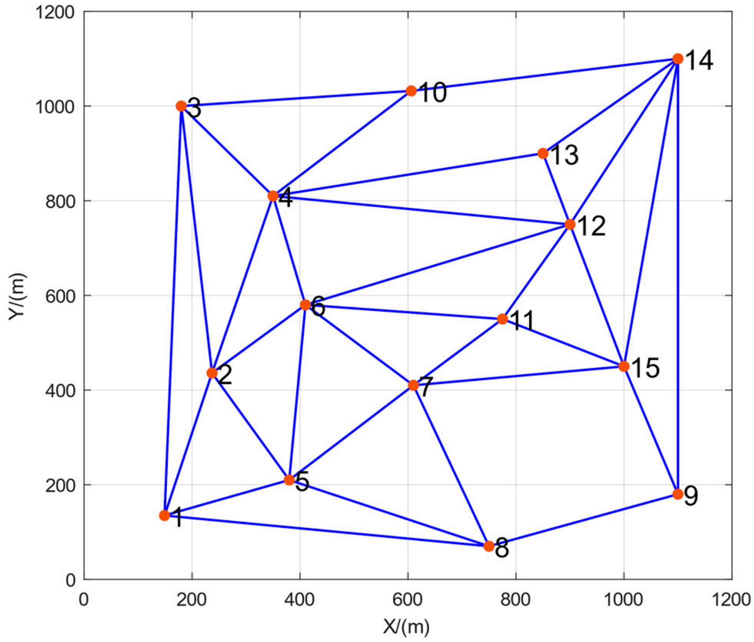

Figure 9. Incomplete environment including 15 task nodes.

Table 5. Expected period of 15 task nodes.

Node	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
T_i (s)	700	750	1050	950	950	850	950	850	700	850	850	750	700	700	750

In order to further evaluate the scalability of the OMACO algorithm, the algorithm is tested in the incomplete environment and the results are shown in Figures 10 and 11. It can be seen that the OMACO algorithm can obtain the optimal path of the UAV swarm in an incomplete environment, satisfying the objective that the actual monitoring period of each node be not higher than the expected period. It can be concluded that the OMACO algorithm can solve the problem of UAV flight paths in different monitoring environments, satisfying the requirements for monitoring overdue events and monitoring privacy.

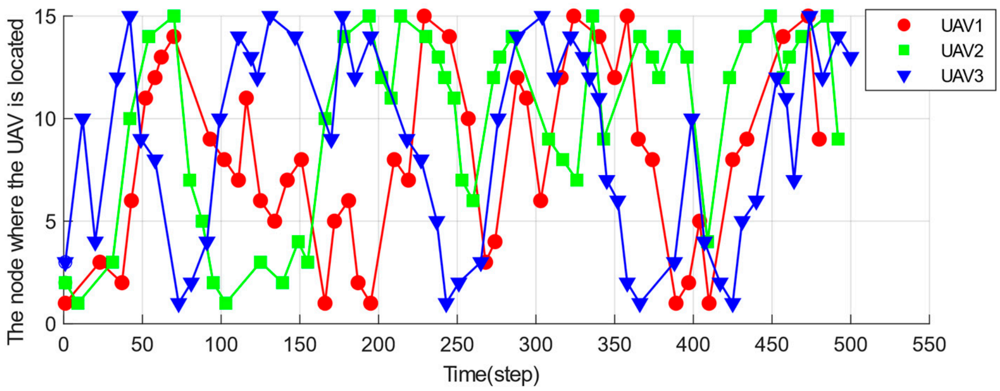

Figure 10. The monitoring path in incomplete environment obtained by OMACO algorithm.

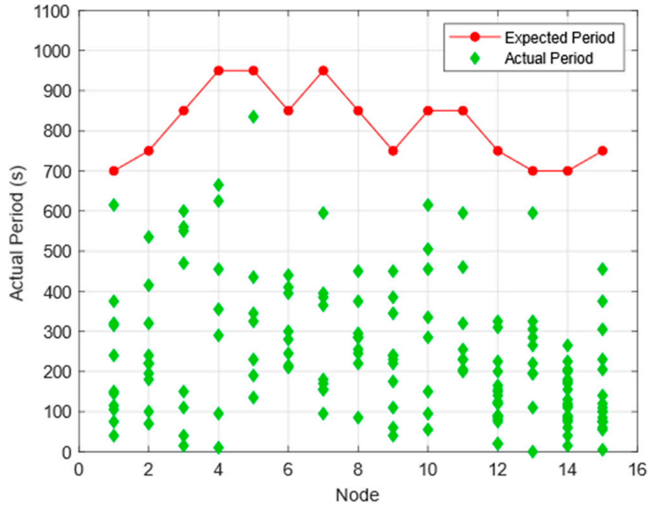

Figure 11. The monitoring period in an incomplete environment obtained by OMACO algorithm.

5. Conclusions

This research has studied the problem of multi-UAV persistent monitoring path planning from the perspective of monitoring privacy protection, reducing monitoring overdue events, and improving the privacy protection of the monitoring trajectory. A multi-UAV path planning mathematical model was established based on the monitoring overdue time and monitoring period entropy. Based on the overdue time, the heuristic function, transition probability and pheromone update, the strategy of the traditional ACO is improved. The simulation results show that the proposed OMACO algorithm can solve the optimal UAV flight path efficiently in both complete and incomplete monitoring environments and has better performance than ACO. This study is promising for the prevention of intelligent intrusions while meeting the requirements of regular monitoring.

However, as the complexity of the monitoring environment increases, there may be adversarial targets destroying monitoring tasks, and the privacy protection requirements may be more stringent. Subsequent consideration will be given to localize adversarial objects cooperatively while executing persistent monitoring assignments.

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