Multi-task Coordinate Algorithm Based on Improved PSO

Ziyang Li, Yufeng Zhuang, Yanzhu Hu*, Wenjia Tian and Song Wang
School of Automation, Beijing University of Posts and Telecommunications, Beijing, China
*Corresponding author e-mail: yzhu@263.net

Abstract. This paper intends to use particle swarm algorithm as the research object of multi-tasking collaborative algorithm. Based on the specific task of multi-UAV distribution at the end of logistics as the background, the model in the task distribution process is constructed. The group modeling process was improved to solve the problem that the coefficient matrix in the task iteration process was discrete and the final result was not the optimal solution. And the task chain is introduced in the algorithm execution process to achieve conflict-free tasks.

1. Introduction
Multi-task collaborative task allocation [1] can reasonably schedule the task execution team, and at the same time, perform scheduling negotiation on special conditions such as working condition saturation, task conflict, lack of capacity, and failure. It is the basic issue for the research of multi-tasking collaborative systems, and it reflects the high-level organizational form and operating mechanism of the system. Therefore, the quality of the task allocation algorithm greatly affects the operating efficiency and actual performance of the multi-task collaborative system.

In order to solve the task assignment problem of multi-task executives, researchers have proposed two main solutions: optimal algorithms and heuristic algorithms. Optimal algorithms are dedicated to solving optimal solutions, including Dijkstra's algorithm, branch and bound method, Hungarian method, dynamic programming, and so on. This method has a high computational complexity and a large amount of calculations, and it is not applicable and feasible under the situation that the scale of the problem is increasing. Heuristic algorithms use mathematical models to solve suboptimal solutions, including genetic algorithms, particle swarm optimization algorithms, and tabu search algorithms. Compared with the optimal algorithm, the heuristic algorithm can obtain a suboptimal solution with excellent performance in a short time when facing large and complex problems. Therefore, researches on tasks such as task assignment mostly use heuristic algorithms. Among them, at the stage of constructing the model, because many task assignment problems generate discrete matrices, it is not entirely suitable to use some heuristic algorithms to solve, and it will cause the final result to be not the optimal solution.

PSO was first proposed as a global random search algorithm based on swarm intelligence by studying the migration and swarming behavior of bird flocks foraging, which is mainly used to solve optimization problems.[3] This thesis intends to use particle swarm algorithm as the research object of multi-task collaborative algorithm, to improve the particle swarm modeling process, and to solve the problem that the coefficient matrix in the task iteration process is discrete and the final result is not the optimal
solution. And the task chain is introduced in the algorithm execution process to achieve conflict-free tasks.

2. Multi-task collaboration algorithm

At present, for the aforementioned heuristic algorithms, many related aspects of multi-tasking collaboration have already mature application environments, such as multi-UAV task allocation problems, robot cart path planning problems, etc., which can achieve their multi-task through heuristic algorithms. The core idea of collaboration.

Aiming at the improved particle swarm algorithm to be adopted, this paper intends to rely on the task assignment problem of multi-UAVs at the end of logistics as the specific background, build a model in the task assignment process, and use the improved particle swarm algorithm to perform task assignment Uniform distribution.

2.1. Optimize task allocation model

At present, domestic and foreign research on UAV task allocation mainly focuses on two aspects: real-time task allocation and task pre-allocation. Real-time task assignment means that during the task execution, the task will change, and the drone needs to respond quickly. Pre-assignment of tasks requires knowing the objectives of the implementation and making an assessment of the information that is available to them.

When a drone performs end-of-logistics distribution, a single distribution task is a point-to-point task, and the task itself is not replaceable. [4] In addition to canceling the distribution during the execution of the task, there will be no task exchange and other phenomena. Based on the particle swarm optimization algorithm, according to its applicable scenarios, comprehensive consideration is given to the task assignment using the pre-assignment method of the aircraft, and the aircraft performs the distribution task in sub-waves.

2.1.1. Basic assumptions of the model

1) Each UAV can only carry one package per wave, and the speed of navigation affected by the weight of the package is not considered.
2) The take-off point of each UAV is fixed.
3) Optimize the model based on distance minimization.
4) This task scenario is terminal distribution of sub-waves, where the time loss caused by switching between waves is uncontrollable, so the time difference caused by switching between waves is not included in the objective function.
5) In practice, there is a limitation on the altitude of the airspace, so all UAV are set to fly at the same altitude. The order of execution of tasks within each wave ensures collision avoidance.

2.1.2. Modeling. Assume that there are $n$ delivery drones $V = \{V_1, V_2, ..., V_n\}$ parked on a fixed delivery take-off platform before the end of the multi-drone delivery task and $k$ package $P = \{P_1, P_2, ..., P_k\}$ that needs to be shipped. The express $P_k$ information is the latitude and longitude of the delivery address $(\text{Longitude}_{k}, \text{Latitude}_{k})$.

The aforementioned aircraft performs flight missions in waves, mainly considering that the number of terminal delivery tasks $k$ should be much larger than the number of unmanned racks $n$, so introduce the wave mechanism, define the current wave order as $w$. When the number of remaining tasks is greater than the number of unmanned racks $n$, $n$ drones are dispatched for each wave, and the tasks within the wave are completed and returned to the distribution platform for the next wave of express package loading. On the one hand, this reduces the actual working time of the loading staff of the distribution center, and on the other hand, improves the accuracy of loading the goods.
2.2. Improved Particle Swarm Algorithm

In the design of the multi-UAV task allocation model, different performance evaluation indexes can be selected. The classic model includes two different evaluation indexes. One indicator is the cumulative flight distance of the drone to complete all tasks, and the other indicator is to minimize the flight time of the drone to complete all tasks. This is because the flight control hardware on which this system is based can cruise at a fixed speed, that is, the drones have the same and constant speed. Therefore, UAV task assignment is to minimize the maximum flight distance of one or more UAVs.

Therefore, this multi-task assignment can be transformed into a problem of objective optimization model. The objective optimization model is an optimization model that uses mathematical programming methods to determine the optimal solution, that is, how to effectively handle resources under the given goals and given constraints. Optimization models are generally composed of three parts: design variables, objective functions, and constraints.

For the $n$ drones of $w$ waves in the above variables, $k$ couriers can form a task allocation matrix $X^{(n \times w) \times k}$. The matrix element $X_{ij}$ is a 0-1 variable, indicating whether the drone $V_i$ of the $w$ wave performs the delivery task of the $P_j$ express, that is:

$$X_{ij} = \begin{cases} 
0, & V_i \text{ not perform tasks } P_j \\
1, & V_i \text{ perform tasks } P_j 
\end{cases}$$

The flight distance matrix $D^{(n \times w) \times k}$ is used to represent the flight distance required for each drone to perform different targets under each wave, as shown below:

$$D = \begin{pmatrix} 
D_{11} & \cdots & D_{1k} \\
\vdots & \ddots & \vdots \\
D_{(n \times w) \times 1} & \cdots & D_{(n \times w) \times k}
\end{pmatrix}$$

Where $D_{ij}$ is the flight distance that drone $V_i$ performs $P_j$.

All the above symbol variables are variables in the multi-UAV task allocation objective optimization model.

The task scenario in this article is the end distribution of sub-waves, where the time loss caused by the switching between waves is uncontrollable, so the time difference brought by the wave switching is not included in the objective function, so the goal of task allocation is to minimize the end Delivery task time. As mentioned above, drones have the same speed throughout the execution of the mission, so the mission completion time can be expressed by minimizing the maximum flight distance of each drone. Then according to the task allocation matrix and flight distance matrix, the task execution time of the drone can be expressed, that is, the objective function that minimizes the task completion time can be calculated using the following formula:

$$\min \max \sum_{j=1}^{k} D_{ij} \cdot X_{ij}, \ i \in V$$

2.2.1. Model Solving Algorithm. At present, scholars at home and abroad have proposed many excellent algorithms for solving the multi-UAV task assignment model. Among them, classic algorithms such as auction algorithms, tabu search algorithms, and genetic algorithms are commonly used. The potential solution of each optimization problem in the PSO algorithm is a particle.[5] All particles share an adaptive value determined by the objective function, which is called the adaptive value function. Each particle has its own speed and position information, which determines its next step. Move direction and distance. PSO initializes a group of random particles and then iterates to find the optimal value. The optimal solution obtained by each particle itself is called the individual optimal value, and the optimal solution obtained by the entire particle swarm is called the global optimal value. The entire particle
swarm updates itself through these two extreme values. Finally, when two adjacent iterations (the difference between the fitness function values) is less than a given threshold or the algorithm reaches the maximum number of iterations, the global optimal value of the particle swarm is returned as the optimal solution of the optimization model. [6]

In the UAV task assignment problem, the optimization goal is to minimize the maximum flight distance of each drone, that is, the fitness function: 

\[ f(x) = \min \max \sum_{j=1}^{k} D_{ij} \times X_{ij}, \ i \in V \]

suppose there are \( N \) particles that make up the particle swarm. Where the \( i \) particle is represented as a \((n * w) * k\) dimensional 0-1 matrix \( X^{(n+w) \times k} \). The matrix has a total of \( n * w \) rows, each row represents a drone within one wave, with \( k \) columns. Each column indicates the task number to be executed. When the element value is 1, the target is executed, otherwise it is not executed, that is:

\[
X_i = \begin{pmatrix}
X_{i1} & \ldots & X_{ik} \\
\vdots & \ddots & \vdots \\
X_{i(n+w)\times 1} & \ldots & X_{i(n+w)\times k}
\end{pmatrix}, \ i = 1,2, \ldots N;
\]

The flying speed of the \( i \) particle is expressed as a \((n * w) * k\) dimensional matrix, which is written as:

\[
V_i = \begin{pmatrix}
V_{i1} & \ldots & V_{ik} \\
\vdots & \ddots & \vdots \\
V_{i(n+w)\times 1} & \ldots & V_{i(n+w)\times k}
\end{pmatrix}, \ i = 1,2, \ldots N;
\]

Among them, each element \( V_{mn}^i \) represents the velocity of the \( m \) row and the \( n \) column in the \( i \) particle.

The optimal position of the \( i \) particle is called the individual optimal value, which is recorded as:

\[
pBest_i = \begin{pmatrix}
pBest_{11} & \ldots & pBest_{1k} \\
\vdots & \ddots & \vdots \\
pBest_{(n+w)\times 1} & \ldots & pBest_{(n+w)\times k}
\end{pmatrix}, \ i = 1,2, \ldots N
\]

The optimal position searched by the entire population is called the global optimal value, which is recorded as:

\[
gBest = \begin{pmatrix}
gBest_{t1} & \ldots & gBest_{tk} \\
\vdots & \ddots & \vdots \\
gBest_{(n+w)\times 1} & \ldots & gBest_{(n+w)\times k}
\end{pmatrix}
\]

The particle updates itself using the following formula:

\[
V_{i}^{t+1} = h * V_{i}^{t} + C_1 * (pBest_{i} - X_{i}) + C_2 * (gBest_{i} - X_{i})
\]

\[
X_{i}^{t+1} = X_{i}^{t} + V_{i}^{t+1}
\]

The first part of the formula can be understood as the previous inertia of the particle, which represents the tendency of the particle to maintain its previous velocity direction and size; [7] the second part is the cognitive behavior of the particle, which is modified according to its previous position, reflecting the particle pair. The memory ability of its own historical experience represents the tendency of particles to move to their own historical optimal position; the third part represents the social behavior of particles, which is updated according to the historical optimal position of the population, reflecting the information sharing and collaborative cooperation represents the tendency of particles to move to the optimal
position of the group. Parameter \( h \) is the inertia factor, and parameters \( C_1 \) and \( C_2 \) are acceleration factors, and their values are uniform random numbers between \([0,1]\)

In the above formula, since \( X_i^{t+1} \) is non-discrete at this time, which is not in line with reality, we pass the mentioned earlier task constraints, and each task is executed only once, which is \( \sum_{j=1}^{k} X_{ij}^{t} = 1 \), do discrete optimization with the non-discrete task execution matrix calculated at this time, and update \( X_i^{t+1} \).

The particle swarm algorithm flowchart is shown in the Figure 1.

![Particle Swarm Algorithm Flowchart](image)

**Figure 1.** Particle Swarm Algorithm Flowchart

### 3. Experiment

#### 3.1. Experimental Design

**3.1.1. Multi-drone Distribution Task Simulation.** For the specific scenario of end delivery, the simulation environment is as follows: The delivery area is a 50 * 50 square area, a total of 3 adjustable UAV can be delivered, and 7 logistics packages need to be delivered. The location of the drone and the latitude and longitude required for the package are shown in Figure 2.

![Simulation environment diagram](image)

**Figure 2.** Simulation environment diagram

Latitude and longitude where the plane takes off:
- \( V_1 \) (0,20), \( V_2 \) (0.25), \( V_3 \) (0,30)

The latitude and longitude required for parcel delivery are:
- \( k_1 \) (16,32), \( k_2 \) (9,11), \( k_3 \) (44,21), \( k_4 \) (35,33), \( k_5 \) (49,7), \( k_6 \) (17,22), \( k_7 \) (42,48)

**3.1.2. Construction of Multi-UAV Task Assignment Model.** According to the optimization of the aforementioned construction model, the flight distance matrix of the model can be expressed as shown in the following table 1 according to the number of aircraft and the number of packages:
Table 1. The flight distance matrix of the model

|     | k₁  | k₂  | k₃  | k₄  | k₅  | k₆  | k₇  |
|-----|-----|-----|-----|-----|-----|-----|-----|
| w₁V₁| 20  | 12.728 | 44.011 | 37.336 | 50.695 | 17.117 | 50.477 |
| w₁V₂| 17.464 | 16.643 | 44.181 | 35.903 | 52.202 | 17.263 | 47.885 |
| w₁V₃| 16.125 | 21.024 | 44.911 | 35.128 | 54.129 | 18.788 | 45.695 |
| w₂V₁| 20  | 12.728 | 44.011 | 37.336 | 50.695 | 17.117 | 50.477 |
| w₂V₂| 17.464 | 16.643 | 44.181 | 35.903 | 52.202 | 17.263 | 47.885 |
| w₂V₃| 16.125 | 21.024 | 44.911 | 35.128 | 54.129 | 18.788 | 45.695 |

3.2. Experimental results

After the introduction of discretization of the aircraft, the mission assignment result largely avoided the non-crossing of the track. The mission sending process took off for the farthest route of the drone and took off first for the longer route, then took off after the closer route, and returned first for the closer route after returning from the longer route, the conflict-free track was achieved through the mission chain. The final reachable matrix results are shown in the following table 2:

Table 2. The final reachable matrix

|     | k₁ | k₂ | k₃ | k₄ | k₅ | k₆ | k₇ |
|-----|----|----|----|----|----|----|----|
| w₁V₁| 0  | 1  | 0  | 0  | 0  | 0  | 0  |
| w₁V₂| 0  | 0  | 0  | 0  | 1  | 0  | 0  |
| w₁V₃| 1  | 0  | 0  | 0  | 0  | 0  | 0  |
| w₂V₁| 0  | 0  | 0  | 0  | 1  | 0  | 0  |
| w₂V₂| 0  | 0  | 1  | 0  | 0  | 0  | 0  |
| w₂V₃| 0  | 0  | 0  | 0  | 0  | 0  | 1  |
| w₃V₃| 0  | 0  | 0  | 1  | 0  | 0  | 0  |

4. Conclusion

This paper proposes a multi-tasking collaborative algorithm based on improved PSO. For the specific task assignment scenario of multi-UAV collaborative terminal distribution, the discrete task allocation matrix generated during the modeling process is discretized, which optimizes the task allocation process, so that the task distribution of the UAV terminal distribution system can obtain the optimal solution to a large extent. And the task chain is introduced in the algorithm execution process to ensure no conflicts between tasks.

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