Multi-UAVs cooperative task assignment and path planning scheme

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Abstract. The task assignment and path planning problems of multiple unmanned aerial vehicles (multi-UAVs) cooperative assistance roadside units (RSUs) for data collection are optimization problems with the goal of minimizing time and energy consumption. This paper proposes a hierarchical optimization scheme for multi-UAVs collaborative assistance RSUs data collection. This solution solves the problems that the number of UAVs needs to be set in advance, the convergence speed is slow when the number of tasks increases, and it is easy to fall into a local optimal solution, and the convergence accuracy is poor. First, the solution uses the K-means algorithm to allocate tasks and group RSUs to find the right number of UAVs to perform the task. Then, this paper proposes a hybrid optimization algorithm based on bionic learning for path planning. Finally, we set up a reasonable evaluation mechanism and conducted simulation experiments. The algorithm in this paper is compared with genetic algorithm, gray wolf algorithm and whale algorithm, the results show that the total cost of the task obtained by the proposed algorithm is the lowest, the algorithm stability is better, and the convergence accuracy is the highest.

1. Introduction

Unmanned aerial vehicles (UAVs) are widely used in military and civilian fields because of their high flexibility, low risk, low cost and easy deployment [1]. In recent years, UAVs have been widely used in the field of intelligent transportation. It will play an important role in traffic detection, road patrol, data collection, emergency communications, traffic accident forensics, target tracking, and transportation [2]. At present, UAVs are basically powered by batteries, so they are constrained by energy consumption and cannot complete large-scale tasks independently. As a result, coordinated execution of tasks by multiple UAVs has become more and more common. In the field of intelligent transportation, the collection of road and traffic data is very important. Currently, wireless sensors or RSUs are deployed to collect information and then transmit the data to the data center. However, in some remote areas, poor areas or some special areas, data collection and transmission will be challenged [3]. Therefore, the use of UAV-assisted RSUs to complete data collection has become an effective method, which will greatly improve the efficiency of data collection [4].

The task assignment and path planning of the cooperative execution of multi-UAVs are important ways to improve the efficiency of UAVs [4]. The multi-UAVs collaborative task assignment is a typical
multiple traveling salesman problem (MTSP), and MTSP is a typical NP problem. Common solution methods are based on Voronoi diagram method [5], fuzzy logic method [6], differential evolution algorithm [7] and so on. However, when the scale of the problem increases, the calculation time will increase exponentially and the efficiency will be low. Therefore, scholars turned to intelligent methods and began to develop approximate algorithms or heuristic algorithms. These algorithms mainly include genetic algorithm [8], simulated annealing algorithm [9], ant colony algorithm [10], particle swarm optimization algorithm [11], etc. These algorithms propose centralized solutions to specific problems, but the algorithms are less universal. At present, most algorithms optimize the task completion time under the premise of a given number of UAVs. In fact, the optimal number of UAVs is unknown in advance. Assuming there are enough UAVs, we need to find the best number of UAVs for a given time limit and task set. For the problem of coordinated execution of tasks by multi-UAVs, if the task is divided into two layers of collaborative optimization, the complexity of the problem can be greatly reduced, and the planning efficiency can be effectively improved. Based on this idea, this paper proposes a hierarchical optimization scheme combining the hybrid gray wolf whale optimization algorithm and the K-means clustering algorithm to solve the task assignment and path planning problems of multi-UAVs. First, the tasks are grouped by K-means clustering algorithm to determine the most suitable number of UAVs to perform the task. Then, with the optimal goal of minimizing energy consumption and execution time, the hybrid gray wolf whale optimization algorithm is used to solve the path planning problem in the group.

The contributions of this article are as follows:

1) A hierarchical optimization scheme for multi-UAVs collaborative assistance RSUs data collection is proposed. First, based on the K-means clustering method for task assignment, the number of UAVs is determined according to the number, location and data size of the RSUs, and the task nodes are grouped.

2) Then, a hybrid gray wolf optimization and whale optimization path planning algorithm is proposed, which enables the UAV in the group to efficiently traverse all the RSUs to complete data collection and achieve the goal of energy consumption and time optimization.

3) Based on the modeling of the data collection problem of the multi-UAVs cooperative assistance RSU, an evaluation mechanism of the task assignment results and the optimal path of the multi-UAVs is proposed.

The rest of this article is structured as follows. Section II specifically describes the requirements and constraints of the problem, explains the meaning of each symbol, and establishes a mathematical model for the specific problem. Section III focuses on the algorithm proposed in this paper, and explains the algorithm's solution process. Section IV verifies the effectiveness and advantages of the algorithm through a large amount of experimental data and result analysis. Finally, Section V summarizes the paper and proposes future research directions.

2. Problem description and mathematical modeling

This paper establishes a mathematical model by minimizing time and energy consumption to complete the data collection of all RSUs. We assume that the UAVs base station coordinate is \( B(x_B, y_B) \). The number of RSUs is \( n \). The coordinate of the \( i \)th RSU is expressed as \( R(x_i, y_i) \). Use matrix \( R \) to store the position coordinates of the RSUs, Then, \( x_i = R_{i1}, y_i = R_{i2} \). Use \( C_i \) to denote the size of the collected data. Establish a distance matrix \( D \), \( D_{ij} \) denotes the distance from the \( i \)th RSU to the \( j \)th RSU. This article sets the maximum flight distance \( L_{max} \), maximum energy value \( P_e \) and average flight speed \( v \) of each UAV as fixed values, and the transmission rate of the UAV is set to \( s \). The number of UAVs in the base station is \( K \), and the number of UAVs selected to perform the mission is \( k \). The acquisition path of the \( k \)th UAV is denoted as \( P_k[B, R_1, ..., R_n, B] \). Figure 1 is a schematic diagram of the problem of multi-UAVs collaborative assistance RSU data collection.
The cost function of multi-UAVs collaborative assistance RSU data collection includes time cost and energy cost. We set the time for the last UAV to perform its mission and return to the base as the mission execution time. The sum of the energy consumption of k UAVs is used as the total energy consumption for mission completion.

The mission execution time of UAVs includes flight time and data collection time. The mission execution time of the kth UAV is specifically expressed as follows:

$$t_k = \sum_{v} D_{ki} + \sum_{s} C_{ki}$$ \hspace{1cm} (1)

In the formula, \(v\) is the average flight speed of the UAV, and \(s\) is the transmission rate of the UAV. \(\sum D_{ki}\) is the flight distance of the kth UAV, and \(\sum C_{ki}\) is the sum of the data size of the RSUs collected by the kth UAV.

The energy consumption of UAVs to perform tasks includes flight energy consumption, hovering energy consumption and transmission energy consumption. Transmission energy consumption is negligible relative to flight energy consumption and hovering energy consumption. Therefore, the energy consumption calculation method of the kth UAV is as follows:

$$e_k = \sum_{v} D_{ki} * p_f + \sum_{s} C_{ki} * p_h$$ \hspace{1cm} (2)

In the formula, \(p_f\) is the flying power and \(p_h\) is the hovering power.

Then the cost function can be expressed as:

$$F = \lambda \sum_{i=1}^{k} F_e^i + (1-\lambda) \max \left[ F_1^i, F_2^i, ..., F_{k+1}^i, F_k^i \right]$$ \hspace{1cm} (3)

Therefore, if the data collection work is to be completed in a short time with low energy consumption, the optimization goal of the problem is \(\min(F)\). Based on the above analysis, we establish the mathematical model as follows:

$$\min \left( F = \lambda \sum_{i=1}^{k} F_e^i + (1-\lambda) \max \left[ F_1^i, F_2^i, ..., F_{k+1}^i, F_k^i \right] \right)$$ \hspace{1cm} (4)

S. t. \(L_i \leq L_{max}\) \hspace{1cm} \(i = (1, 2, ..., k)\) \hspace{1cm} (5)

\(F_e^i \leq F_e^i\) \hspace{1cm} \((i = 1, 2, ..., k)\) \hspace{1cm} (6)

\(k \leq K\) \hspace{1cm} (7)

\(P_1 \cap P_2 \cap \cdots \cap P_k = B\) \hspace{1cm} (8)

\(P_1 \cup P_2 \cup \cdots \cup P_k = B, R_1, R_2, ..., R_n\) \hspace{1cm} (9)
Equation (5) ensures that the flying distance of each UAV does not exceed the maximum flying distance. Equation (6) ensures that each UAV can have enough energy to complete the task. Equation (7) ensures that the number of UAVs selected does not exceed the number of UAVs in the base station. Equation (8) ensures that the data of each RSU is only collected by one UAV. Equation (9) ensures that the data of each RSU can be collected by a UAV.

3. Algorithm solution

The data acquisition problem of multi-UAVs cooperative assistance RSU is a combinatorial optimization problem, which belongs to NP complete problem. When the problem is large, it is difficult to find the optimal solution in a short time. In addition, the strong coupling of multi-UAVs collaborative task assignment also increases the difficulty of solving the problem. Therefore, an effective solution for multi-UAVs collaborative assistance RSU data collection is to design heuristic or super-heuristic algorithms to find the optimal or sub-optimal solution in a reasonable time.

According to the problem model, the solution ideas of this paper are as follows: First, the RSUs are grouped by the K-means algorithm. Then, use the algorithm proposed in this paper to solve the traveling salesman problem in each group. In this paper, gray wolf algorithm [12] and whale optimization algorithm [13] are mixed, which is called Hybrid Grey Wolf and Whale Optimization Algorithm (HGWOA). First of all, the algorithm uses the whale algorithm in the exploration stage, because the whale algorithm uses a logarithmic spiral update, it can perform a more extensive global search in the early stage. Second, replace the position of the global optimal solution sought by the gray wolf algorithm with the position of the whale, the whale optimization algorithm guides the wolves to converge to the optimal solution, reducing the calculation time. Therefore, mixing the best features of the gray wolf algorithm and the whale algorithm makes the probability of finding the global optimal solution higher, and also avoids the algorithm from stagnating or falling into the local optimal. The HGWOA combines the advantages of the gray wolf optimization algorithm in the development phase and the whale optimization algorithm in the exploration phase to obtain the global optimal solution. The mathematical model of HGWOA is as follows:

According to the hierarchy of the gray wolf algorithm, the three solutions with the highest fitness value will be saved in each iteration, which are alpha, beta, and delta in order. The spiral update equation of the whale optimization algorithm is used to update the positions of alpha, beta, and delta to improve the convergence performance of the gray wolf algorithm. The gray wolf algorithm and the whale algorithm have the same other operations. The position update model of the spiral update equation for alpha, beta and delta is as follows:

\[ Q = X_0^* + D \cdot e^{ih} \cos(2\pi l) \]  
\[ D_a = |C_1 \cdot X_a - Q|, \quad D_\beta = |C_2 \cdot X_\beta - Q|, \quad D_\delta = |C_3 \cdot X_\delta - Q| \]  
\[ X_1 = |X_a - A_1 \cdot D_a|, \quad X_2 = |X_\beta - A_2 \cdot D_\beta|, \quad X_3 = |X_\delta - A_3 \cdot D_\delta| \]  
\[ X_{t+1} = \frac{X_1 + X_2 + X_3}{3} \]

In the formula, \( D = |X_0^* - X| \) represents the distance from the individual to the prey, \( b \) is a constant defining the shape of the logarithmic spiral, and \( l \) is a random number \([-1,1]\).

In the whole iterative process, by controlling parameters such as \( a, A, C, \) and \( p \), the algorithm can fully perform a global search in the early stage, and the algorithm will accelerate the convergence in the later stage, and the individual position is updated as follows:

\[ X_{t+1} = X_t - A \cdot D, \quad |A| \leq 1, \quad p < 0.5 \]  
\[ X_{t+1} = \left( X_1 + X_2 + X_3 \right)/3, \quad |A| \leq 1, \quad p \geq 0.5 \]  
\[ X_{t+1} = X_{t,\text{rand}} - A \cdot D_{\text{rand}}, \quad |A| > 1 \]
4. Experimental results and analysis
In this section, we will provide simulation results to prove the effectiveness and superiority of the algorithm proposed in this paper. Combined with the above model and algorithm, the programming simulation is carried out in the MATLAB environment. We consider a 10km×10km urban area, the base station location is \( B(1,1) \), and the total number of UAVs is 5. Set the number of RSUs to 50. We set the same weight for energy consumption cost and time cost, set the number of drones to 2, 3, 4, and 5. Since the algorithm uses random initialization, in order to better demonstrate the convergence effect, this paper uses the average of the algorithm's 30 convergence results as the final convergence result. The convergence result is shown in Figure 2.

![Figure 2. Convergence results for different numbers of UAVs.](image)

It can be seen from the figure that when the number of RSUs is 50 and the number of UAVs is 4, the minimum total overhead will be obtained.

In order to verify the effectiveness of the algorithm, this paper compares the optimization effects of genetic algorithm, gray wolf algorithm, and whale algorithm on the data collection of multi-UAVs collaborative assistance RSUs. Similarly, this time the average value of 30 simulations of the algorithm is used as the final convergence result. The convergence result is shown in Figure 3.

![Figure 3. Convergence results of the four algorithms.](image)

It can be seen from Figure 4 that when the number of RSUs is 50 and the number of UAVs is 4, the four algorithms basically converge at 1000 iterations. The algorithm proposed in this paper achieves a lower total cost, and the convergence speed and accuracy are better than the other three algorithms. It can be seen that the algorithm proposed in this paper has faster convergence speed and higher convergence accuracy when solving the problem of multi-UAVs collaborative assistance RSU data collection.

In order to compare the stability of the optimization effect of the four algorithms, in the above scenario, the four algorithms were respectively subjected to 30 simulation experiments, and the optimal solution, worst solution, average solution, and variance obtained are shown in Table 1:

|           | GA   | GWO  | WOA  | GWOA |
|-----------|------|------|------|------|
| Worst     | 88.5526 | 87.6864 | 86.9987 | 83.0840 |
| Best      | 83.2931 | 81.5624 | 80.0617 | 77.4095 |
| Mean      | 85.8257 | 84.7138 | 83.9286 | **80.0726** |
| Std       | 1.6671 | 2.2238 | 2.2286 | **1.9579** |

It can be concluded from Table 1 that the genetic algorithm has the worst convergence accuracy, but the smallest variance, so the algorithm has good stability; the gray wolf algorithm and the whale algorithm have poor convergence accuracy and stability. The algorithm proposed in this paper is better than the gray wolf and whale algorithm in terms of convergence accuracy and stability, and slightly worse than the genetic algorithm in terms of stability. Obviously, when the algorithm proposed in this article solves the problem of multi-UAVs collaborative assistance RSU data collection, its convergence
speed and convergence accuracy are higher than the other three algorithms. And the algorithm also has better algorithm stability, and is more suitable for solving such problems.

5. Conclusion and future work

This paper proposes a data collection strategy for multi-UAVs collaborative assistance RSUs. First, we use the K-means algorithm to find the appropriate number of UAVs to perform the task according to the number, location and data size of the RSUs. Then, a hybrid gray wolf whale optimization algorithm was proposed to plan the data collection path of the roadside units in the group, and set the cost function model of the trade-off between delay and energy consumption. Finally, the algorithm proposed in this paper is compared with genetic algorithm, gray wolf algorithm, and whale algorithm. The simulation results show that under the set scenario, the algorithm proposed in this paper has faster convergence speed, better stability and higher convergence accuracy. In future work, we are committed to further research from the following aspects: on the one hand, improve the stability of the hybrid algorithm; on the other hand, using deep reinforcement learning algorithms to solve such problems.

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