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RESEARCH ARTICLE

Multi-UAV Reconnaissance Task Allocation in 3D Urban Environments

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ABSTRACT This paper considers a reconnaissance task allocation problem for multiple unmanned aerial vehicles (UAVs) in 3D urban environments. In this paper, we present an extended heterogeneous targets reconnaissance task allocation model which introduced cuboid targets for 3D urban environment to improve the fidelity of the model. A reconnaissance method is designed for each type of target, and the mission is described as a heterogeneous target multi-traveling salesman problem model for solving complex optimization problems with multiple constraints.To address these complex optimization problems, multi-group symbiotic organisms search algorithms (MGSOS) are proposed, which maintain the diversity of species in the population through multi-group strategies and enhance information exchange between individuals in three stages. Real-number encoding is used to satisfy partial constraints and simplify the search space, improving the optimization efficiency of the solution. The simulation results show that the MGSOS algorithm can consider the characteristics of UAV sensor performance and heterogeneous targets. It outperforms the common symbiotic organisms search (SOS) algorithm in terms of the optimality of assignment results, and is suitable for larger scale urban reconnaissance task allocation problems.

INDEX TERMS 3D urban environment, generalized multi-traveling salesman problem, np-hard problem, symbiotic organisms search, task allocation, unmanned aerial vehicle.

I. INTRODUCTION

As urban warfare increasingly becomes a vital form of modern conflict, utilizing multi-UAV for rapid reconnaissance in 3D urban environments has become an essential strategy. The irregular topography, densely packed buildings, and constrained airspace inherent in urban environments demand specialized task allocation strategies. Multi-UAV collaborative reconnaissance is a typical mission for better target finding and information acquisition. Task allocation is an important problem in multi-UAV reconnaissance mission, which can allocate necessary tasks and determine the appropriate task execution sequence to the UAVs to minimize system cost efficiently and maximize overall performance. Researchers on multi-UAV task allocation primarily focus on problem modeling and algorithm innovation.

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The basic task allocation problem that aims to find the shortest flight path can be formulated as multi-traveling salesman problem (MTSP) [1] or a vehicle routing problem (VRP) [2] model for solution. It is also necessary to optimize UAV's locations or trajectories [3], [4], [5]. In Chen et al. [6], the authors addressed the path planning issue for UAVs with varying capabilities in multi-region systems. Optimal paths were provided for UAVs to effectively visit all regions. The coverage path planning problem of heterogeneous UAVs was also studied, with the authors identifying optimal flight paths for each UAV from the start region to the end region, ensuring sequential coverage of all regions of interest in the shortest time [7]. Based on these studies, the energy consumption constrained scheduling problem of workflows in heterogeneous multi-processor systems was addressed, and a three-phase scheduling algorithm to ensure the correct and efficient running of tasks was proposed [8].To address the system constraints of UAVs, the Dubins path model is combined with the traveling salesman problem (TSP) to obtain the Dubins TSP (DTSP) model [9]. Considering the effective range of UAV sensors, the Dubins traveling salesman problem with neighborhood (DTSPN) model is proposed [10]. Some targets are time-sensitive, and the UAV flight path may be affected due to the target time window constraint. In this case, the task is described as a TSP with time window (TSPTW) model [11]. Additionally, the cooperative multiple task assignment problem (CMTAP) model is proposed to describe the performance of classify, attack, and verify tasks on UAVs [12]. Although algorithms for solving these problems have been extensively studied, the task allocation problem is often significantly simplified when using these models without considering the nature of the problem. Wang et al. [13] first considered the heterogeneity of targets, and Cheng et al. [14] similarly considered targets with heterogeneous features and sizes to propose the Dubins multi-traveler problem based on time windows, but these models only considered differences between targets at the stage of entering and leaving after allocation. Gao et al. [15] present a novel mathematical model that classifies heterogeneous targets as point targets, line targets and area targets to improve the fidelity of the model. However, in 3D urban environments, there exist a number of high-rise topographic features on the ground, such as buildings and ground architecture [3], the model that classifies heterogeneous targets as point, line and area targets is not comprehensive.

Within urban environments, due to the obstruction of various structures, the distribution of targets cannot be directly perceived as lying on a single plane, nor can the sensing direction of UAV sensors be solely directed downwards. Thus, the issue of UAV reconnaissance in urban environments cannot be fully explained with a 2D model. In this paper, we consider target characteristics and dimensions in a 3D sense within urban environments and establish a UAV reconnaissance model. Targets are categorized as point, line, area, and cuboid targets, each represented by different feature points.

The task allocation problem is a classic NP-hard combinatorial optimization problem. Algorithms for solving this problem can be categorized into two groups: optimization methods and heuristics methods. The optimization Methods like the branch and bound(BNB) method [16] and dynamic programming(DP) [17] can find local optimal solutions for low-dimensional problems, but struggle to find feasible solutions as the number of UAVs and targets grows due to the exponential increase in computational cost. In contrast, the heuristics methods with low computational complexity can effectively obtain workable solutions, primarily used for addressing combinatorial optimization problems. Including the genetic algorithm (GA) [18], simulated annealing (SA) algorithm [19], gravitational search algorithm (GSA) [20], ant colony optimization (ACO) algorithm [21], particle swarm optimization algorithm(PSO) [22], shuffled frog leaping algorithm, bacterial foraging optimization, artificial bee colony(ABC) algorithm [23]. New algorithm structures are used or the advantages of different algorithms are combined to improve the quality and search speed of candidate solutions [24], [25]. A comprehensive review paper on swarm intelligence algorithms has been published, covering various optimization techniques [26]. The reallocation in emergent scenarios has been reported by [27]. To solve the problem of reallocation, Tang et al. utilized the clustering of UAVs based on fuzzy C-means (FCM), along with ACO. In addition, Cheng and Prayogo [28] introduced the symbiotic organisms search (SOS) as a meta-heuristic optimization algorithm to extensively explore potential solution spaces. This approach has gained significant traction in the fields of numerical optimization and engineering design [29], and has shown promise in addressing UAV mission assignment challenges [30].

Urban environments are complex and have a very large number of targets, while urban operations should reduce civilian casualties and reduce the destruction of buildings. Therefore, efficient and precise mission execution is required, and the high number of targets requires a large number of UAVs to perform the mission. With the increasing size of UAVs and the number of targets, the efficiency and convergence quality of heuristic algorithms are more demanding. The SOS algorithm is used to solve task allocation problems due to the advantages of easy implementation, parallelizability, strong search capability, and wide applicability. It is suitable for solving the optimal search problem in complex space. However, in high-dimensional spaces like urban environments, the SOS algorithm still suffers from the problems of falling into local optimum and precocity. In this paper, we propose a new Multiple-Group Symbiotic Organisms Search (MGSOS) algorithm to solve the multi-UAV reconnaissance task allocation in 3D urban environments problem. In MGSOS, The biological population is divided into two subpopulations, each designated for exploring and developing the optimal solution. By reinforcing individual guidance, improved algorithmic exploration capabilities can be achieved.

This paper's main contributions are as follows. Firstly, an extended heterogeneous targets reconnaissance task allocation model which introduced cuboid targets for 3D urban environment is presented. Secondly, the task is described as an extended generalized multiple traveling salesman problem (GMTSP) model. To improve the solution quality and search efficiency of the assignment plan, a multi-group symbiotic organisms search algorithm to solve the multi-UAV reconnaissance task allocation model is proposed. Improvements are applied to the symbiotic, coeval, and parasitic phases of the SOS to enhance information interaction among individuals, improving the algorithm's search performance. Additionally, a real number encoding method is employed to address variable constraint relationships, reducing the search space and enhancing search efficiency. Finally, we experimentally analyze the performance of our algorithm and conduct comparative experiments of different

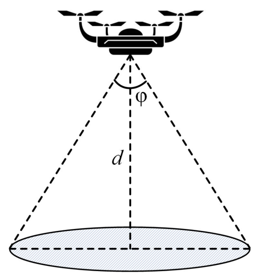


FIGURE 1. Field of view of sensors.

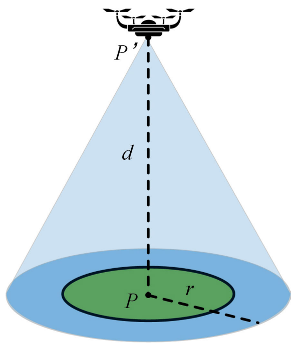


FIGURE 2. Schematic diagram of point target.

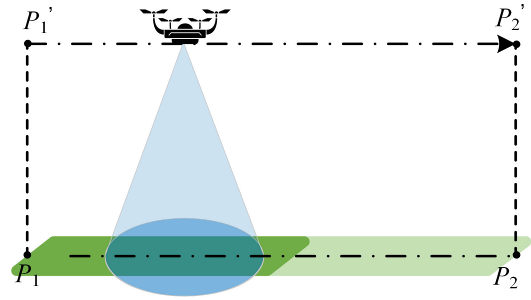


FIGURE 3. Schematic diagram of line target.

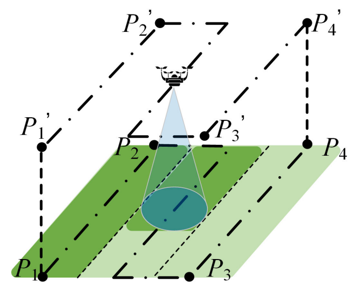


FIGURE 4. Schematic diagram of area target.

scale scenarios. The results demonstrate that our algorithm has superior capability.

II. RECONNAISSANCE MISSION MODELING IN URBAN 3D ENVIRONMENT

The UAV needs sensors for collaborative target reconnaissance in the city. In this study, the sensor view is considered as a circular area facing the plane where the target is located, as shown in Fig. 1. d is the distance between the UAV and the target plane. When the target is on the ground, d is the flight height of the UAV. φ is the field of view of the sensor. When the target area is completely covered by the field of view of the sensor, the target reconnaissance is completed. To simplify the model, the field of view of the sensor is assumed to be unaffected by the flight height and attitude of the UAV.

A. TARGETS MODEL AND RECONNOITER STRATEGIES

In general, an important feature of the target is the target shape. To facilitate the calculation of the target detection time and flight path, the target shapes in the 3D urban environment are classified as point targets, line targets, area targets, and cuboid targets. The detection time of the same UAV is different due to the different sizes of the targets. Flight paths between targets are planned using the A* algorithm. The path is planned from the starting point to the destination point based on pre-existing obstacle information and free area data in the prior map to avoid static obstacles.

1) POINT TARGET

A point target is a target smaller than the UAV detection range r, as illustrated in Fig. 2. Typical point targets include vehicles and enemy personnel. A feature point P is used to represent the position of the point target. When the UAV flies over the center of a point target, the reconnaissance task for a point target is performed, and the position of the UAV is represented by P'.

2) LINE TARGET

Line targets are indicated as having a length greater than the reconnaissance width $2r$ of the UAV but a width less than the reconnaissance radius of the UAV. As shown in Fig. 3, the best way for the UAV to reconnoitre a line target is to leap along the longest path of the target centerline. Therefore, the line target has two entrances (P_1 and P_2 in Fig. 3) which results in different exit locations but the same reconnaissance path length for the UAV. So it is also necessary to consider the distribution of target entrances in the flight path of the UAV.

3) AREA TARGET

For the area target, its length and width are larger than the UAV detection width. To obtain complete information about the target, this paper uses the "zigzag" shortest path method to reconnoitre the area target as shown in Fig. 4. Four feature points indicate area targets. For an area target, there are two "zigzag" paths, as shown in Fig. 5, which h_1 and h_2 are the two side lengths of the rectangle. The shortest path can be chosen by (1), with L denoting the distance of the shortest path. When considering the reconnaissance problem, different entrances need to be selected.

$$L = \min\left\{h_2 + \left\lceil \frac{h_2}{2r} \right\rceil \cdot h_1,\ h_1 + \left\lceil \frac{h_1}{2r} \right\rceil \cdot h_2\right\} - 2r \quad (1)$$

where $\lceil\cdot\rceil$ is upward rounding function.

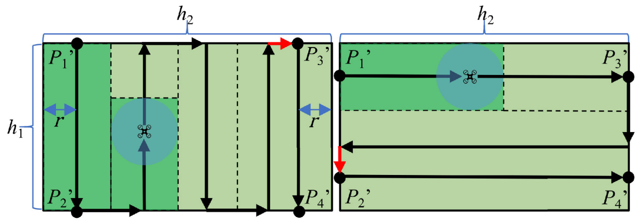


FIGURE 5. Illustrating two coverage paths for the area target.

4) CUBOID TARGET REPRESENTATION AND SCOUTED STRATEGY

For cuboid targets, the height of the target is considered, which is greater than the reconnaissance width of the UAV. Generally, large buildings are considered as cuboid targets, so they carry information about the number of floors f_r, as shown in Fig. 6. Eight feature points indicate cuboid targets. In this paper, the reconnaissance is carried out around the cuboid target as shown in Fig. 7, where $m_1 = h_3/2f_r$ and $m_2 = d$. It can be seen from Fig. 7 that there are eight entrances to the rectangular target, but the reconnaissance paths are of the same length and are calculated as shown in (2).

$$L = (h_1 + h_2 + 4d) * 2f_r + h_3 * \frac{f_r - 1}{f_r} \tag{2}$$

B. PROBLEM DESCRIPTION AND FORMULATION

The drones perform a reconnaissance mission before the mission area identifies N_T suspicious or high-risk targets using other technical methods, requiring the use of N_V drones in the mission area to reconnoiter the targets. The UAVs were assigned to reconnoiter all the targets in the shortest possible time and with the lowest consumption. In this paper targets are heterogeneous, characterizing the location and shape features where a target is located by multiple feature points, in other words, these feature points collectively represent a target. Targets can be classified as point, line, area and cuboid. According to the targets model and reconnoiter strategies proposed in Section II, when the entry point of a target is known, the exit point is uniquely determined. The mission execution cost can be divided into two parts: the sum of the range of all UAVs performing the mission, and the maximum time to complete the scouting mission. When reconnoitering a target, the UAV needs to select the entrance to the target in addition to considering the order of execution of the target. Therefore, this paper describes this mission assignment problem as the GMTSP problem.

The GMTSP problem can be represented on a fully empowered graph $G = (P, E, W)$, where P is a set of vertices, each vertex represents a feature point of a target or a feature point of a take-off location(the takeoff location can be represented by one feature point, similar to the point target), which means P is also a set of feature points. E is a set of arcs, representing a set of all edges with vertices connected two by two, and W is a set of weights, representing the distance between any two vertices in the graph G. Take $T =$ $\{T_1, T_2, \ldots, T_{N_T}\}$ as a set of targets, $V = \{V_1, V_2, \ldots, V_{N_V}\}$ as a set of drones, and $D = \{D_1, D_2, \ldots, D_{N_D}\}$ as a set of takeoff locations, where $D \subseteq T$(the takeoff position is considered as the point target). $P = \{P_1, P_2, \ldots, P_{N_P}\}$ is a set of N_P points, with each point belonging to a target in the set T, therefore, there exists a mapping relationship $f : P \mapsto T$. The number of feature points N_P can be obtained from (3).

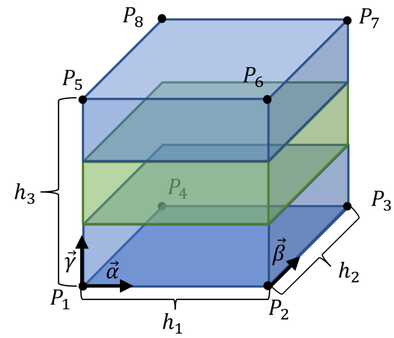


FIGURE 6. Schematic diagram of cuboid target.

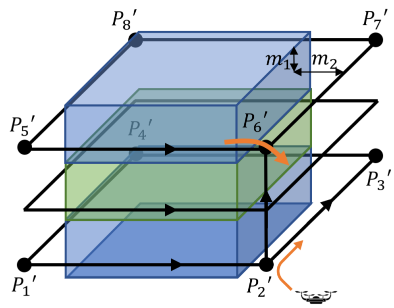


FIGURE 7. Illustrating a coverage path for the area target.

$$N_P = \sum_{i=1}^{N_T} |T_i| + \sum_{j=1}^{N_D} |D_j| \tag{3}$$

The path planning algorithm obtains the path set E between feature points and the distance matrix W. The objective of the mission is to conduct a reconnaissance of all targets and then return to the takeoff location, while minimizing both fuel consumption and the overall duration of the mission. In this paper, the multi-objective optimization problem is solved using the weighted summation method, and the evaluation function of the assignment result is given by (4) [17]. The GMTSP problem is to find a set of optimal decision variables $X^{V_i}_{(c_m,c_n)}$ to minimize (4).

$$\min J = \alpha \cdot \max_{V_i \in V} R_{V_i} + \beta \cdot \sum_{i=1}^{N_V} R_{V_i} \tag{4}$$

where $\alpha, \beta \in [0, 1]$ are the weights of the two optimized indicators and $\alpha + \beta = 1$. R_{V_i} denotes the total range cost of the reconnaissance mission of the drone V_i, which is calculated as shown in (5).

$$R_{V_i} = \sum_{m=1}^{N_P}\sum_{n=1}^{N_P} X_{(P_m,P_n)}^{V_i} W(P_m, P_n) + \sum_{m=1}^{N_P}\sum_{n=1}^{N_P} X_{(P_m,P_n)}^{V_i} L_{T_*=f(P_n)}, \quad i = 1, 2, \ldots, N_V \quad (5)$$

The first component involves the drone's travel distance between targets. P_m and P_n are two points in the set P, $X_{(p_m,p_n)}^{V_i}$ is a decision variable indicating whether drone V_i travels from P_m to P_n (1 if it does, 0 otherwise). W is the path cost matrix, $W(P_m, P_n)$ denotes the distance of the flight path of the UAV from P_m to P_n. The second component accounts for the path cost while scouting the next target, $L_{T_*=f(P_n)}$is the path cost scouting the target T_*, where T_* is the image of P_n under the mapping relationship f in the set T.

Moreover, to ensure that all targets can be reconnoitered and that each target can only be detected once, the following constraint is imposed on the allocation problem.

$$\begin{cases} \sum_{i=1}^{N_V}\sum_{m=1}^{N_P} X_{(P_m,P_n)}^{V_i} = 1 \ , n = 1, 2, \ldots, N_P \\ \sum_{i=1}^{N_V}\sum_{n=1}^{N_P} X_{(P_m,P_n)}^{V_i} = 1 \ , m = 1, 2, \ldots, N_P \\ X_{(P_m,P_n)}^{V_i} = 0 \ , P_m \in D_k; P_n \in D_l \ (k, l = 1, 2, \ldots .N_D) \\ X_{(P_m,P_n)}^{V_i} = 0 \ , P_m, P_n \in T_j \ (j = 1, 2, \ldots, N_T) \end{cases} \quad (6)$$

The first constraint guarantees each target is detected once. Similarly, the second constraint guarantees that each target is detected. Meanwhile, the third constraint ensures UAVs cannot fly directly between each other's takeoff feature points. The fourth constraint restricts UAVs from flying between points within the same target.

III. OPTIMIZATION ALGORITHM DESIGN

For the traditional SOS algorithm, its guidance strategy is to approach the best individuals in the population, which results in a better exploitation capability but a relatively weak exploration capability. The lack of exploration capability is the main factor that leads the algorithm to fall into local optima. Therefore, a multi-group strategy is adopted to divide the population into subpopulations, and assign them with separate exploration and exploitation tasks.

A. REAL NUMBER CODING DESIGN WITH LOW VARIABLE DIMENSIONALITY

Flexible coding of organisms can effectively reduce the complexity of the problem. The task assignment solution needs to contain the serial numbers of the drones, the serial numbers of the targets, and the order of execution. Therefore, a low-dimensional real number encoding approach is used in this paper. Each dimension on the real vector corresponds to each target from left to right and is associated with the index of the drone in the integer part. The magnitude of the corresponding decimal part is used to represent the execution order of the target in the task sequence. Each creature is an n-dimensional real vector. The vector is encoded by real numbers to represent a solution to the task assignment. According to the encoding method, the dimensionality of the real vector $n = N_T$ and the range of values in the real vector is $[0, N_V)$. This encoding allows the UAV to assign results that contain each target and the target is not repeatedly reconnoitered, satisfying the constraints mentioned in the model. For the same UAV, the target exit is determined when the entrance to the target is determined. In this paper the entrance of the target is selected using the shortest distance flown, so GMTSP is transformed into MTSP.

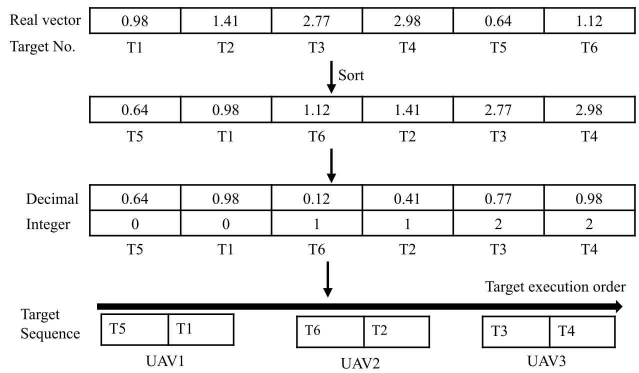


FIGURE 8. Real number encoding process.

Fig. 8 shows an example of real number encoding. There are 6 targets and 3 drones. The dimension of the real vector is 6 and the range of values is [0,3). The candidate organisms can obtain the following task sequence after being encoded using real numbers:

$$\text{UAV1} \Rightarrow \{T_5 \rightarrow T_1\},$$
$$\text{UAV2} \Rightarrow \{T_6 \rightarrow T_2\},$$
$$\text{UAV3} \Rightarrow \{T_3 \rightarrow T_4\}.$$

B. MULTI-GROUP SYMBIOTIC ORGANISMS SEARCH ALGORITHMS (MGSOS)

The specific approach is to divide the symbiotic population into two subpopulations of equal size based on the high and low fitness values of the organisms. The subpopulation with higher fitness values serves as the elite subpopulation, whereas the one with lower fitness values serves as the exploration subpopulation. The organisms in the elite subpopulation have a small difference in fitness values compared to the global best individual and work together with the best individuals to enhance their exploitation capability. The organisms in the exploration subpopulation have a large difference in fitness values compared to the global best individual, and thus are not suitable for exploiting the search space. However, due to their better diversity, their individual information can be utilized to improve the algorithm's exploration capability and compensate for the lack of exploration capability in the traditional SOS algorithm.

For the mutualistic phase, in addition to the current organism X_i, one organism X_e is randomly selected from the elite subpopulation and one organism X_s is randomly selected from the exploration subpopulation. The organism X_e from the elite subpopulation is responsible for exploitation, whereas the organism X_s from the exploration subpopulation is responsible for exploration. The current organism X_i interacts with the organisms X_e and X_s randomly according to the mechanism of the traditional algorithm in the mutualistic symbiosis stage. The updated method of the mutualistic symbiosis stage after improvement is shown in (7)–(10).

$$MV1 = \frac{X_i + X_e}{2} MV2 = \frac{X_i + X_s}{2} \tag{7}$$

$$X_i^{\text{new}} = \begin{cases} X_i + \text{rand}(0, 2) \times (X_{\text{best}} - \text{MV1} \times \text{BF1}), & r < m \\ X_i + \text{rand}(0, 2) \times (X_{\text{best}} - \text{MV2} \times \text{BF2}), & r \geq m \end{cases} \tag{8}$$

where X_{best} is the global optimal biology, $BF1$ and $BF2$ are mutual benefit factors equal to 1 or 2, r is a random number between 0 and 1, and m is an artificially set threshold, which is usually taken as 0.5 to have better results.

Elite creatures undertake exploitation tasks, mainly interacting with the optimal creatures and searching near the optimal creatures.

$$X_e^{\text{new}} = \begin{cases} X_{\text{best}} + \text{rand}(0, 2) \times (X_e - \text{MV1} \times \text{BF1}), & r < m \\ X_{\text{best}} + \text{rand}(0, 2) \times (X_{\text{best}} - \text{MV1} \times \text{BF2}), & r \geq m \end{cases} \tag{9}$$

Exploring populations exploit their diversity and interact with organisms X_i to achieve global exploration.

$$X_s^{new} = MV2 + rand\,(0, 2) \times (X_s - MV2 \times BF3) \tag{10}$$

In the traditional Commensalism phase, an organism X_j is randomly selected and the best organism X_{best}'s bootstrap information about organism X_j is used to update the current organism X_i. This stage does not fully utilize the individual information of other high-quality organisms, so we use the better-adapted individuals in the elite subpopulation to guide the current organism X_i, which improves the convergence speed of the algorithm whereas also using a certain degree of diversity in the elite population to maintain the exploration ability in this stage. The improved deviation from the symbiotic stage is updated as shown in (11).

$$X_i^{new} = X_i + rand\,(-1, 1) \times (X_e - X_i) \tag{11}$$

For the parasitism phase, the traditional parasitism phase method parasitizes a randomly selected organism X_j by mutating X_i. During the iteration of the algorithm, since X_i traverses the whole population, often most of the organisms do not have a superior fitness value, and it is difficult to obtain a parasitic organism with a superior fitness when mutating them. Therefore, we have decided to restrict the mutation phase to the elite subpopulation. As the elite subpopulation has higher fitness values, individuals have a greater chance of obtaining high-quality organisms through mutation. The specific implementation method is to use the current organism Xi as the host and select an individual from the elite subpopulation for mutation, resulting in a parasitic organism Pa. Finally, the fitness levels of the two organisms are compared, and the winner is retained.

C. PROCEDURE OF MGSOS

The pseudo-codes of MGSOS are shown in Algorithm 1.The procedure of MGSOS algorithm for solving 3D urban environment multi-UAV reconnaissance task allocation problem is as follows:

Algorithm 1 MGSOS for 3D Urban Environment Multi-UAV Reconnaissance Task Allocation Problem

Initialize ecosystem with N_p, target N_t
Set *runningTime*, *startTime*
Calculate fitness: $f(X_i)$, X_{best}
while *nowTime*−*startTime* < *runningTime* **do**
  for $i = 1$ to N_p **do**
    /* Mutualistic Phase */
    Randomly select X_e, X_s
    Calculate $MV1$, $MV2$
    for $k = 1$ to N_t **do**
      Update X_i^{new}, X_e^{new} conditionally
      Perturb X_s^{new} randomly
    end for
    if $f(X^{new}) < f(X)$ **then**
      Update X
    end if
    /* Commensalism Phase */
    for $k = 1$ to N_t **do**
      Update X_i^{new} commensally
    end for
    if $f(X_i^{new}) < f(X_i)$ **then**
      Update X_i
    end if
    /* Parasitism Phase */
    for $k = 1$ to N_t **do**
      if rand(0, 1) < rand(0, 1) **then**
        Update $X_{parasite,k}$
      end if
    end for
    if $f(X_{parasite}^{new}) < f(X_i)$ **then**
      Update X_i
    end if
  end for
  Calculate fitness: $f(X_i)$, X_{best}
end while
return X_{best} as solution

Step 1: Initialize the ecosystem with the number of organisms N_p. Set the target number to N_t. Set the algorithm's running time as *runningTime* and the start time as *startTime*.

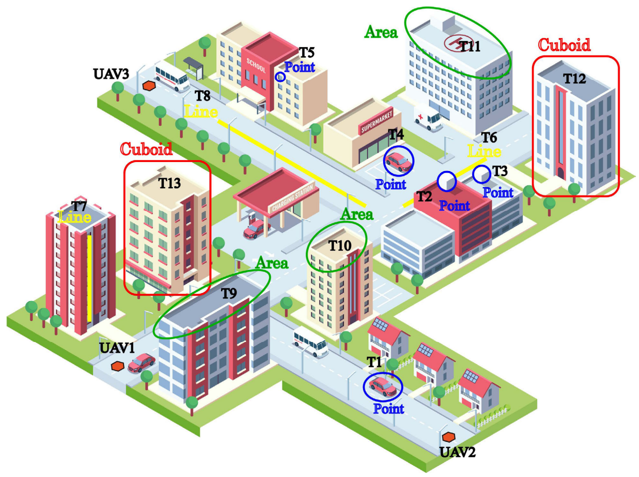


FIGURE 9. Distribution of drones and targets in the city.

The fitness value of each organism was calculated according to $f(X_i)$ and the best organism was selected as X_{best} from it.

Step 2: The better half of the ecosystem is considered as the elite population and the rest as the exploratory population according to the fitness value of the organisms.

Step 3: Each organism$X_i$in the ecosystem is subjected to three phases of mutualistic, commensalism, and parasitism, respectively.

Step 4: The fitness value of each organism was calculated according to $f(X_i)$ and the best organism was selected as X_{best} from it.

Step 5: If NFE is less than max_NFE, the process jumps to Step 2; otherwise, output the current X_{best} as the result and the iteration process stops.

IV. SIMULATION AND ANALYSIS

In this section, the multi-UAV task allocation algorithm is validated through simulation experiments and compared with other methods of multi-UAV task allocation problem through comparison tests. The simulation is run in a Python environment on a PC with Intel(R) Core(TM) CPU i7-11800H 2.30 GHz and 16 GB RAM hardware configuration and running Windows 10 operating system. Table 1 shows the key parameters of the simulation phase.

The field of view of the sensor φ is set to be 50 deg; the weight factors α and β of the two optimized indicators are both set to be 0.5. To simplify the model, the distance between the UAV and the target plane d is set to be 10m.

A. URBAN ENVIRONMENTAL RECONNAISSANCE TASK SIMULATION EXPERIMENT

First of all, we validate the proposed model. The initial positions of the 3 UAVs are (3,116,0), (56,3,0), and (129,226,0). In the current scenario, 13 different types of targets exist, and the details are shown in Table 2. The Table 2 presents information about different targets with corresponding numbers, types (point, line, area, cuboid), and

TABLE 1. Parameters related to the MGSOS algorithm.

Parameter	Location	Value
φ	Section 2.1	50 deg
d	Section 2.1	10 m
Vehicle Speed	-	10 m/s
α	Eq. (4)	0.5
β	Eq. (4)	0.5

TABLE 2. Target attributes.

Target No.	Target Type	Feature Points	Target No.	Target Type	Feature Points
1	Point	1	8	Line	2
2	Point	1	9	Area	4
3	Point	1	10	Area	4
4	Point	1	11	Area	4
5	Point	1	12	Cuboid	8
6	Line	2	13	Cuboid	8
7	Line	2			

their respective feature point counts. For example, Target No. 1 is a point with 1 feature point, whereas Target No. 12 is a cuboid with 8 feature points.

The distribution of the targets is given in Fig. 9, where the blank areas are unknown, and the UAVs will not pass through these dangerous areas for flight safety in mission planning.The assignment results are calculated using MGSOS, and the resulting task sequence for the UAV is as follows:

$$\begin{aligned}
\text{UAV1}: &\ T7[1] \rightarrow T9[7] \rightarrow T13[8] \\
\text{UAV2}: &\ [t]T10[1] \rightarrow T6[1] \rightarrow T11[1] \\
&\ \rightarrow T3[1] \rightarrow T2[1] \rightarrow T1[1] \\
\text{UAV3}: &\ T5[2] \rightarrow T4[6] \rightarrow T12[1] \rightarrow T8[1]
\end{aligned}$$

The numbers in square brackets denote entry positions during target reconnaissance, corresponding to feature points defined in target modeling. For example, in the UAV1 sequence, T7[1] indicates UAV1 starts at the first feature point of target T7, and then proceeds to survey T9 and T13. Similarly, for UAV2, T10[1] signifies entry at the first feature point of T10, followed by reconnaissance of other targets in the specified order.

Fig. 10 shows the convergence curve of the algorithm, which provides insights into how the MGSOS algorithm progresses towards finding optimal solutions, showcasing its effectiveness and efficiency. Fig. 10 (a) shows how the fitness value changes as the algorithm iterates, shedding light on the algorithm's ability to improve the quality of solutions. Fig. 10 (b) shows the algorithm's impact on minimizing total distance of the drone swarm mission, whereas Fig. 10 (c) shows its influence on reducing maximum time consumption of the drone swarm mission.

The range cost of each drone is UAV1: 1187.6 m; UAV2: 505.2 m; UAV3: 1768.41 m. Under the current allocation, the total range of all the UAVs flying the mission is 3461.2 m, and the maximum time for mission completion is 176.8 seconds.

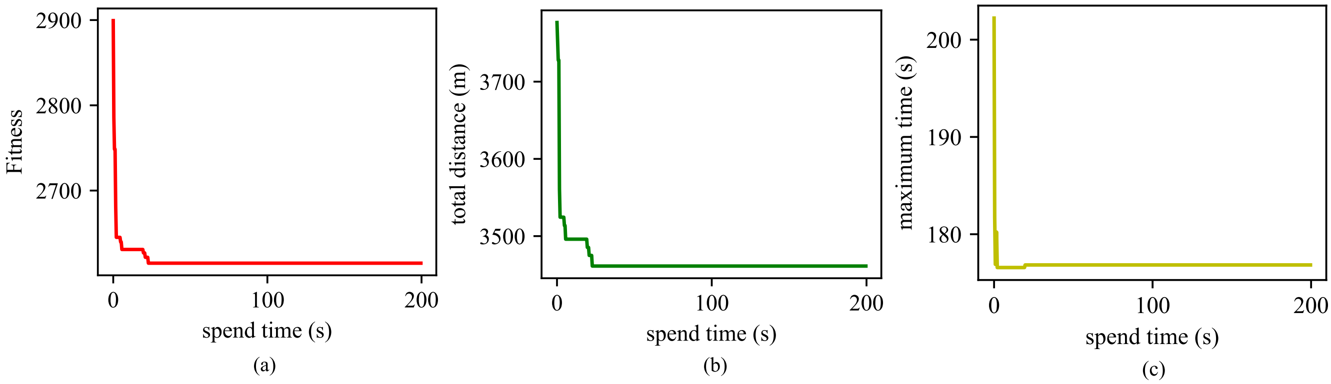


FIGURE 10. Convergence curve of fitness and indicators.

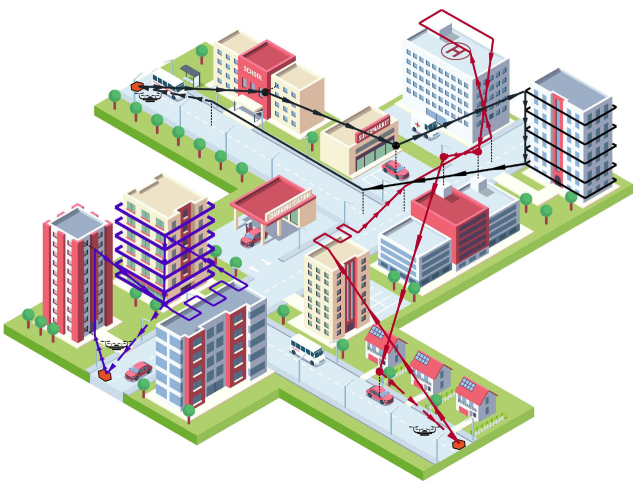


FIGURE 11. UAV trajectory in task assignment results.

The trajectories of the UAVs according to the assignment results are shown in Fig. 11, with UAV1's trajectory in purple, UAV2's trajectory in red, and UAV3's trajectory in black.

Fig. 11 shows the navigation path of the UAV based on the assigned results, and it is known that the UAV reconnoitered all the targets and performed a full coverage reconnaissance of point, line, surface, and cuboid targets. Considering the shortest total range, the shortest maximum time to complete, the heterogeneity of the targets and the safe flight path, the UAV reasonably visited each target. Among all targets, reconnaissance of rectangular type T12 and T13 required the greatest time and range cost, where T13 was assigned to UAV1, which was closest to it. Compared to UAV3, UAV2 was further away from T12 due to the unknown area or exclusion zone on the right side of the map, so target 12 was assigned to UAV3; target 11 was a little closer to UAV3, but the total range cost of UAV2 is not high, so assigning it to UAV2 is a better choice. From the range cost of each UAV, we can see that the allocation result makes the cost consumption of each UAV more balanced. Overall, the proposed task allocation model and the improved algorithm proved feasible and effective.

TABLE 3. Algorithm parameters.

Algorithm	Parameter
SOS	/
OGA-DEMMO	Pc=0.6; Pm=0.2
GA-PSO	w=0.8; c1=2; c2=2; r1=0.6; r2=0.3; k=0.0; P1=0.4; P2=0.5; P3=0.5
MGSOS	/

TABLE 4. Number of UAVs and targets at different scales.

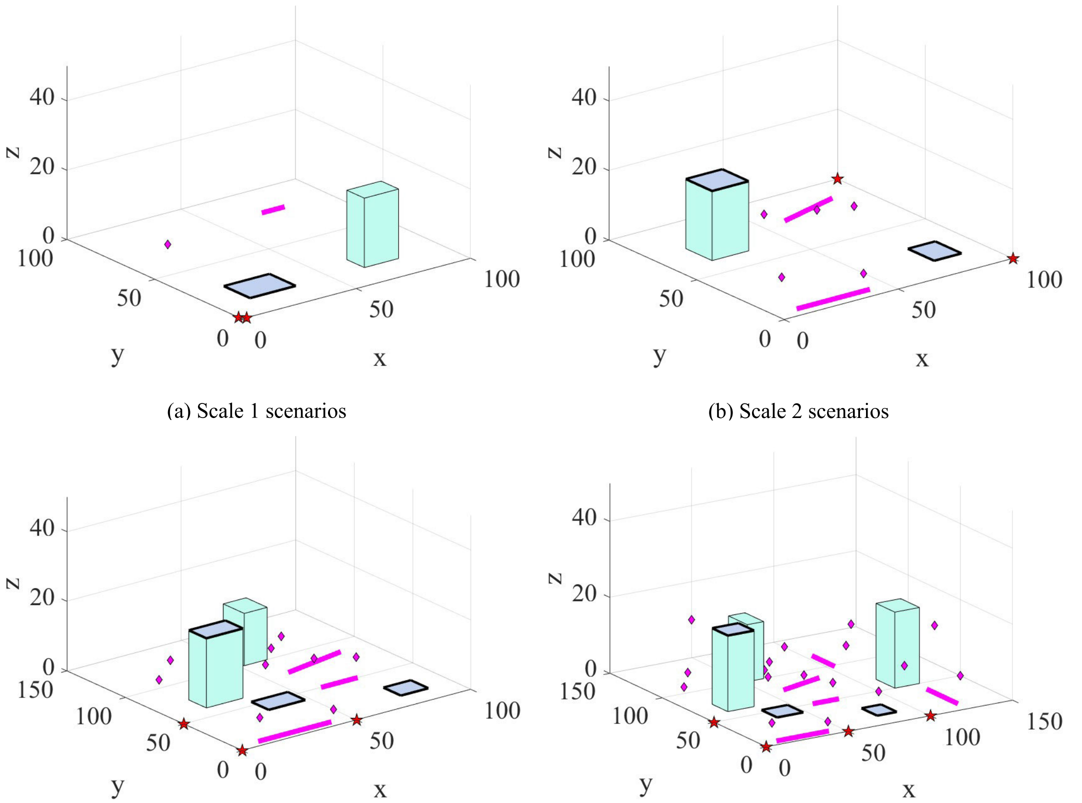
Scale ID	NV	Point No.	Line No.	Area No.	Cuboid No.
1	2	1	1	1	1
2	2	5	2	2	1
3	3	10	3	3	2
4	4	20	5	3	3

B. ALGORITHM COMPARISON ANALYSIS

To verify the superiority of the improved algorithm, four algorithms are compared and analyzed. The proposed MGSOS algorithm is compared with the conventional SOS algorithm, the Opposition-based Genetic Algorithm using Double-chromosomes Encoding and Multiple Mutation Operators (OGA-DEMMO) algorithm [13], and the GA-PSO algorithm, where the OGA-DEMMO is an improved task assignment optimization algorithm for such reconnaissance tasks mentioned in this paper, and the GA-PSO algorithm is also used to calculate an assignment solution for a certain task assignment problem. A more efficient algorithm would complete its training and generate a workable solution in less time [8]. The detailed parameters of these algorithms are listed in Table 3.

The task scenarios were divided into four scales based on the number of different types of targets, as shown in Table 4. The scale is increasing due to the rise in UAV numbers and targets. In this simulation, each algorithm runs 50 times for each scenario and set the same running time as a stopping criterion to get statistical results.

In Fig. 12, scale 1–4 represents the four scales of distribution of UAVs and heterogeneous targets in space, where the diamond markers are point targets, the lines indicate line targets, the rectangles with thickened borders



(a) Scale 1 scenarios

(b) Scale 2 scenarios

(c) Scale 3 scenarios

(d) Scale 4 scenarios

FIGURE 12. UAV and target distribution at different scales.

TABLE 5. Comparison of statistical results of the four algorithms.

Scale ID	Pop size Max NFE	SOS			GA-PSO			OGA-DEMMO			MGSOS		
		min	mean	max	min	mean	max	min	mean	max	min	mean	max
1	20,2	794.1	794.1	794.1	794.1	794.1	794.1	794.1	796.0	811.2	794.1	794.1	794.1
2	30,10	896.7	901.5	915.8	896.7	900.4	911.4	896.7	917.6	996.0	896.7	898.8	901.9
3	40,120	1206.6	1263.0	1297.0	1204.1	1264.5	1327.2	1239.4	1299.0	1379.9	1190.6	1240.7	1301.9
4	50,500	1940.8	2064.8	2167.2	1921.2	2126.4	2385.1	1802.1	1942.3	2063.8	1751.1	1853.6	1966.9

indicate area targets and the cubes indicate cuboid targets. The ideal detection position of the UAV is set directly above the target. Table 5 shows the results of 50 independent runs of the four algorithms under the same conditions. Under scales 1, 2, 3, and 4, the population sizes are 20, 30, 40, and 50, respectively, with maximum NFEs of 2, 10, 120, and 500. A total of four scales were tested, and the algorithms had the same running time at each scale. Fig. 13 shows the convergence of the four algorithms in different scenarios. The curves show the average level of the algorithms after 50 independent runs.

For scale 1, the results of MGSOS, SOS, and GA-PSO solutions are the same. The fitness value of the allocation scheme obtained by OGA-DEMMO is 1.9 more than that of the first three algorithms. According to the fitness calculation formula (4), it can be seen that the OGA-DEMMO algorithm performs slightly worse but not significantly. In scale 2, after 10 seconds of computation for each algorithm, all algorithms gradually converge to a stable value. From Fig. 13(b), we can see that the MGSOS algorithm has the fastest convergence speed, as well as the best convergence result. The GA-PSO and OGA-DEMMO algorithms also have a faster convergence speed, but the quality of the solution scheme after convergence is not as good as that of MGSOS. The SOS algorithm also searches for a better allocation scheme, but its convergence time is relatively longer. In scale 3, MGSOS, GA-PSO, and OGA-DEMMO algorithms all have faster convergence speeds. However, MGSOS has stronger search capability and search accuracy compared with the other two algorithms and gets a better convergence solution before convergence. In the scale 4 scenario, MGSOS has a faster convergence speed and stronger search capability compared to the other algorithms and reaches a better solution in a short time. As the computation time increases, the MGSOS exploration mechanism makes it possible to improve the accuracy of the results as much as possible.

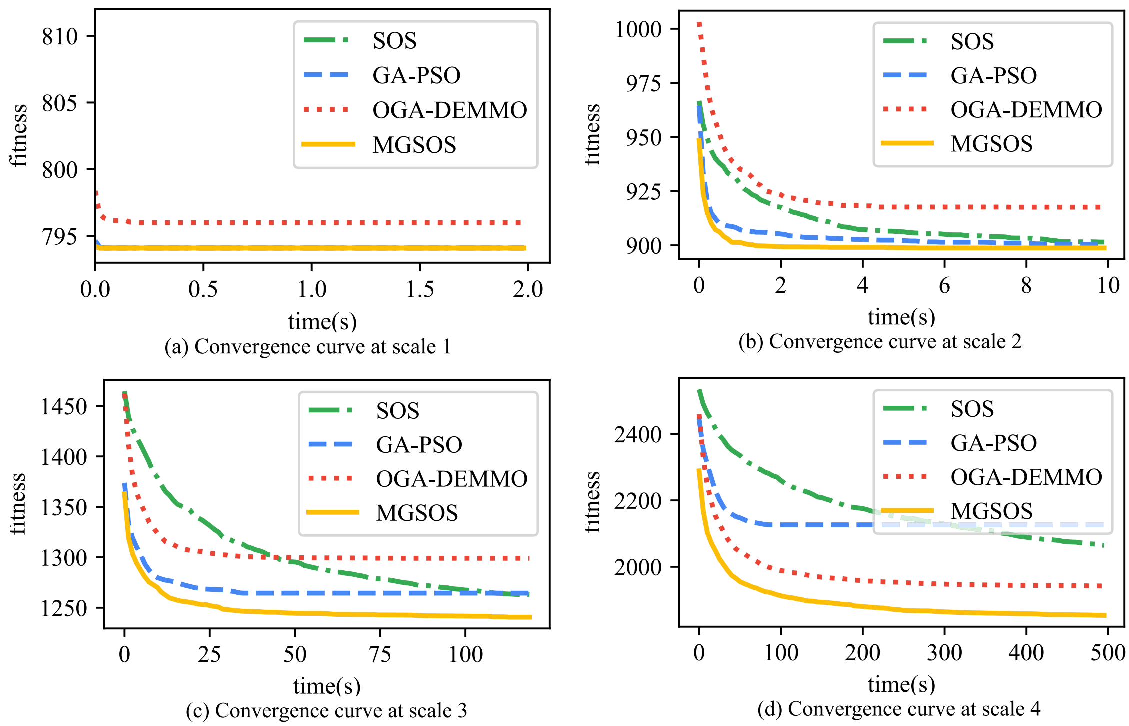


FIGURE 13. Convergence curves of four algorithms at different scales.

Overall, The MGSOS algorithm outperforms the other three algorithms in both optimization capabilities and stability. It is noticeable that with an increasing scale, the MGSOS algorithm exhibits a superior advantage in terms of average fitness values. In Scale 4, the fitness value of MGSOS is 10.23% better than SOS, 12.8% better than GA-PSO, and 4.57% better than OGA-DEMMO. The MGSOS algorithm has the fastest convergence speed and the strongest optimality finding capability among the comparison algorithms. The algorithm can obtain a better assignment solution than the other compared algorithms in the shortest time and has a strong ability to jump out of the local optimum and continuously optimize the assignment solution as time increases. Therefore, the MGSOS algorithm has significant advantages over the other three algorithms in solving the UAV reconnaissance task assignment problem in urban environments.

V. CONCLUSION

In this study, a new 3D urban UAV reconnaissance model is proposed. Targets are classified into point, line, area, and cuboid targets based on their geometric characteristics, and are represented using different numbers of feature points. The optimization objective is to minimize the weighted sum of the total UAV consumption and the task execution time. An improved SOS algorithm is proposed to solve GMTSP. Using real number encoding to describe the result of UAV assignment to targets. The algorithm is improved using multiple swarm strategies to maintain biological diversity and enhance the information interaction among individuals in the three phases to improve the algorithm's optimality and convergence efficiency. Numerical experiments of different scale scenarios validate the effectiveness of MGSOS. It is also compared with GA-PSO and OGA-DEMMO algorithms. The results show that the MGSOS algorithm can provide a better quality task assignment solution to the multi-UAV reconnaissance problem of heterogeneous targets of 3D urban environments.

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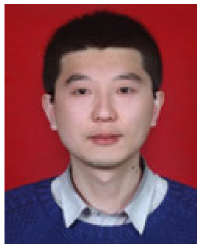

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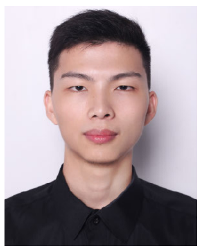

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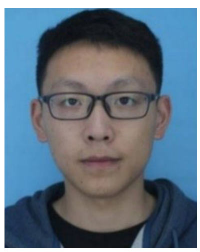

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