Type of the Paper (Article, Review, Communication, etc.)

Distributed Multi-target Search-Track Mission Planning for Unmanned Aerial Vehicles in Uncertain Environment

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**Abstract:** A single paragraph of about 200 words maximum. For research articles, abstracts should give a pertinent overview of the work. We strongly encourage authors to use the following style of structured abstracts, but without headings: (1) Background: Place the question addressed in a broad context and highlight the purpose of the study; (2) Methods: briefly describe the main methods or treatments applied; (3) Results: summarize the article’s main findings; (4) Conclusions: indicate the main conclusions or interpretations. The abstract should be an objective representation of the article and it must not contain results that are not presented and substantiated in the main text and should not exaggerate the main conclusions.

**Keywords:** keyword 1; keyword 2; keyword 3 (List three to ten pertinent keywords specific to the article yet reasonably common within the subject discipline.)

1. Introduction

With the increasingly complex and changeable mission environment, multiple unmanned aerial vehicles (UAVs) have been used to form a cooperative combat system with complementary advantages and cooperation in reconnaissance mission areas to improve the overall combat capability of UAVs in complex and changeable battlefield situation environment[1]. UAV swarm system is inspired by swarm intelligence derived from the biological swarm behavior in nature such as the behavior of ants and bees which is coordinated and controlled according to the swarm intelligence principle, making full use of its local perception and interaction ability to complete relatively complex tasks. Meanwhile, as the number of UAVs increases, their computational and communication complexity increases dramatically. Moreover, the UAV swarm has high requirements for system robustness, communication reliability, and capacity. The distributed control architecture is widely used which adopts an autonomous and collaborative approach and can divide the complex problem into sub-problems that can be solved by UAV at each node, giving full play to the autonomous capability of each UAV and greatly improving the compute efficiency, such as search and rescue (SAR)[2], surveillance[3], civil security[4], search[5-7], task allocation[8], mapping[9] and so on.

In cooperative mission planning, sometimes we need to maintain continuous surveillance of a target until it loses its value, while maintaining a search of the entire area to find additional potential targets or to handle special situations. In this regard, cooperative path planning and task assignment are mainly considered for multiple UAVs. For path planning, Shao et al. [10] proposed an improved particle swarm optimization algorithm that improves the quality of path solutions by using chaos-based logistic mapping to improve particle initialization and using constant acceleration coefficients and maximum velocity as adaptive learning factors. Kumar et al. [11] proposed an advanced fuzzy ant colony algorithm to improve the efficiency of path planning by classifying the pheromone update scheme into two categories, i.e., favorable and unfavorable paths. For task assignment, Qing-Song Ye et al [8] clustered multiple targets to solve for the target clusters from the dispersed targets, and then distributed the resulting target clusters to different UAV formations to complete the formation-level target assignment process. Zhang et al [27] incorporated two contract bids based on contract nets and introduced a concurrent transaction mechanism to enhance the algorithm's ability to handle multi-task assignments.(换一下)

While many significant efforts have been made to address each problem separately, few researchers have solved the integration problem that combines the search and tracking problems. In the case of the search-track integration problem, Wang and Hussein[12] considered the problem of tracking all discovered targets and searching for new targets simultaneously by controlling the pointing direction of the vision sensors and the motion of the UAV, but only one UAV was used in this research work. Skoglar et al [13] proposed a coordinated control technique that allows heterogeneous vehicles to search and track multiple targets automatically using recursive Bayesian filtering. The UAV can switch its operation mode from search to tracking. However, the proposed algorithm is centralized. Meng et al.[14] proposed a control framework based on a finite-state automaton model to deal with the multi-UAV search and tracking task planning problem, however, this approach fails to consider the synergy among multiple UAV, especially when the tracking task needs to be considered after the discovery of a target. Some other related studies have focused on UAV path planning for target tracking[15, 16]

Motivated by these facts, we propose a novel approach to adapt to the challenges posed by the collaborative integrated search-track problem. 在发现目标前，无人机集群需要对任务环境进行覆盖式搜索，一旦无人机集群搜索编队发现目标，则无人机集群的任务 性 质 发 生 变 化，即 从 纯 粹 的覆盖式搜索转为在搜索和对已发现目标进行跟踪。提高无人机资源利用，提高搜索效率。

In addition, optimization algorithms including traditional and intelligent optimization formulate the search mission planning problem as finding the optimal solution while satisfying various optimization conditions and constraints. Many traditional optimization algorithms, such as convex optimization and gradient descent, are widely used. For example, reference[17] presents a method that generates time-optimal trajectories rapidly via convex optimization. reference[18] proposed an improved gradient algorithm to solve the problem of trajectory optimization problem. However, even for stationary targets and a single UAV, this search problem is considered NP-hard[19] which causes large time consumption using traditional optimization methods. Therefore, computational intelligence algorithms[20] inspired by nature mechanisms approach such as Genetic Algorithm (GA)[21], Particle Swarm Optimization (PSO)[22], Ant Colony Optimization (ACO)[7], Pigeon-Inspired Optimization (PIO)[23] and so on, are great efficiency for solving such complex problems. Computational intelligence algorithms do not attempt to traverse the entire search space due to its heuristic random characteristics, but consider the optimal performance of computation time and solution simultaneously, to obtain a better solution within acceptable time and computation cost[24]. Shima T et al.[25] use GA to solve the UAV swarm cooperation problem, and the simulation results show that GA can achieve better search results in a shorter time than the traditional optimization method, but the convergence speed of the algorithm is still low. To solve the problem of slow convergence of GA, Zhang and Hu [26] added a gravity search mechanism in individual update links to improve the convergence speed of algorithm and applied the improved the algorithm to solve the problem of multi-UAV cooperative reconnaissance task. Zhen, Ziyang[27]（换文献）proposed a cooperative mission planning scheme for multiple UAVs by hybrid artificial potential field and ant colony optimization (HAPF-ACO) method for UAVs to search and attack moving targets in uncertain environments. Zheng et al.[28] proposed a biogeographic-based optimization (BBO) method to minimize the expected time for aid workers to reach the target for the problem of human-UAV cooperative search planning and experiments show that the algorithm is superior to many popular algorithms. Duan and Zhao[23] propose a dynamic discrete pigeon-inspired optimization (D2PIO) algorithm to handle cooperative search-attack mission planning for UAVs, and achieved well experimental results.

However, all the above-mentioned literatures focus on the improvement of optimization algorithms to avoid falling into local optima and speed up the convergence process, thus improving the search efficiency. Most search methods are short-sighted and they only focus on the largest value of the objective function in the current candidate raster, i.e., they only consider the information of a single raster or a single point without considering the information of the whole region. Therefore, UAVs can easily waste search resources by frequent region shifting, and the whole search process falls into local optimum.

Different from the results in above references, the main contributions are as follows:

2. Cooperative search-track problem description

In this section, the cooperative search-track mission will be modeled and the mission environment will be established. Meanwhile, the search-track mission planning problem will be defined, and the constraints of search-track mission planning model will be given.

2.1 Cooperative Search-Track Model of UAV Swarm

This paper aims to solve the problem of searching and tracking M dynamic targets in an unknown region by N heterogeneous UAVs, as shown in Figure 1. The problem is modeled as an optimization problem with multiple constraints. The objective function is determined based on the goals of the mission, and the flight rules constitute the constraints of the problem.

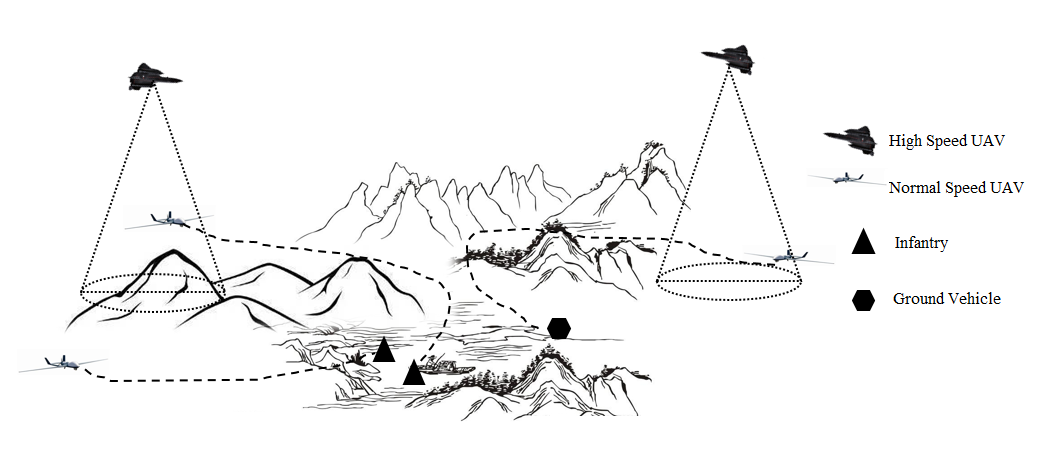
At the beginning of the mission, the UAVs are deployed in the mission area and each UAV performs a coverage search of the area following a real-time online planned path. Once the UAV swarm finds the target, the nature of the UAV swarm’s mission changes from the coverage search to the search and tracking of the found target. By planning the next waypoint of the UAVs, the search and tracking efficiency is maximized during the mission, resulting in better execution performance.

(When the UAV swarm searches for targets in an unknown environment, the optimal flight path of the UAV swarm needs to be planned online according to the latest environment. By planning the next waypoint of the UAV swarm, we can ensure that the search and tracking efficiency is maximized during the mission, resulting in better execution performance. （问题描述这里参考搜索跟踪这一篇再好好改一下）

本文旨在解决由N个异构无人机在未知区域搜索和跟踪M个动态目标的问题，如图1所示。该问题被建模为一个具有多个约束条件的优化问题。目标函数是根据任务的目标确定的，而飞行规则构成了问题的约束。在任务刚开始时，UAV被部署用于搜索和跟踪移动目标的区域，各无人机按照实时规划的航路对区域进行覆盖式搜索，一旦无人机集群发现目标，则无人机集群的任务 性 质 发 生 变 化，即 从 纯 粹 的覆盖式搜索转为搜索和对已发现目标进行跟踪。通过规划无人机群的下一个航点，保证在任务中搜索和跟踪效率最大化，从而获得更好的执行性能。

当无人机集群发现目标时，无人机对目标的追踪收益也被考虑，通过规划无人机群的下一个航点，保证在任务中搜索和跟踪效率最大化

当无人机群在未知环境中搜索目标时，需要根据最新环境在线规划无人机群的最佳飞行路径。提高无人机资源利用，提高搜索效率。)



**Figure 1.** Illustration of UAV swarm search and tracking dynamic targets

Define the status of the UAV swarm as:





whereis the state of UAV. The purpose of cooperative search-track of UAV swarm is to cover the mission area, find and track more targets under the given constraints. Therefore, surveillance benefit  and the target tracking benefit  are the performance indicators of the cooperative search-attack mission. To describe the search-track mission, the objective function of this problem is defined as follows:





where  is the decision input which represents the waypoints of the UAV swarm in the next iteration.  represents the surveillance efficiency about the whole area of the UAV swarm. represents the tracking efficiency of the UAV swarm, and  represents a set of constraint items.

For the distributed control structure, each sub-UAV is equipped with a separate processor to build its own solution, so that the centralized search-track mission planning indicator can be transformed to be a distributed form.





where  represents the set of the neighboring UAVs under the same communication topology.  =1 means UAV  is performing the search task, namely:



so the UAV will minimize uncertainty in the mission area and search the mission area with maximum surveillance coverage to detect most targets as quickly as possible.

When a target is uncovered, the benefits of tracking this target need to be considered by the UAV. While the target is kept in the UAV’s field of vision, the UAV continues to explore the environment, namely:







where  is the state of target . UAV adjust its motion state according to the target's speed to keep tracking. During the tracking mission process, UAVs continuously update the environment information within the detection range and share the detection information with other UAVs within the communication range.

The global objective function  is formulated as:



2.2 Uncertainty Map Pyramid Model of The Environment

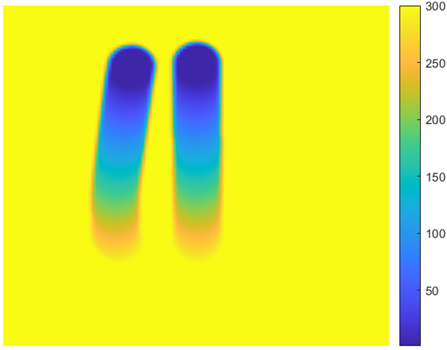
Due to the complicity time-vary mission area, the characteristics of the target and the goal of our mission should be taken into consideration while modeling the environment, and the initial motion state of targets are unknown. When targets are in stationary state, the problem can be described as a simply maximum coverage problem without consideration of the searched area. When targets are in moving state, they may move to the previously detected area. Therefore, the environment is modeled using a time varying uncertainty map [文献39] to ensure the UAV swarm completing the task of search and tracking of all targets. Each UAV keeps an uncertainty map  which is divided into a two-dimensional grid . According to the prior information of the mission, we get the information of the grid as follows:



where  represents the uncertainty of target in cell  at time . is the coordinate of the grid. The uncertainty of a grid indicates its probability of a hiding a target, which depends on how long it has been since it was last detected and the prior mobility of target:



where  is the time elapsed from the last time it was searched. When , it means that the grid is within the current detection radius of the UAV, and the uncertainty of the grid is zero. The uncertainty of the grid increases with time and the rate of change is determined by the memory factor which depends on the prior velocity  of target. For a single UAV, its uncertainty map is shown in **错误!未找到引用源。** after a period time. At the beginning, the whole area is not detected and the uncertainty is high. The process of searching the map by UAV swarm is to turn the uncertainty in the map into certainty.



**Figure 2.** Uncertainty grid map of a single UAV

A single level of uncertainty map is not sufficient to represent the whole information of the mission area. Information at different scales also contributes to the understanding of the environment. Aiming to get a larger global view, the image pyramids initially used in computer vision is a series of images arranged in a pyramid shape with gradually decreasing resolution from the same original image. In some image processing algorithms, the multi-resolution operation of image pyramid can avoid falling into local points and enhance the robustness. The multi-resolution operation is also applied in grid map of geographic information system to speed up the display of grid data.

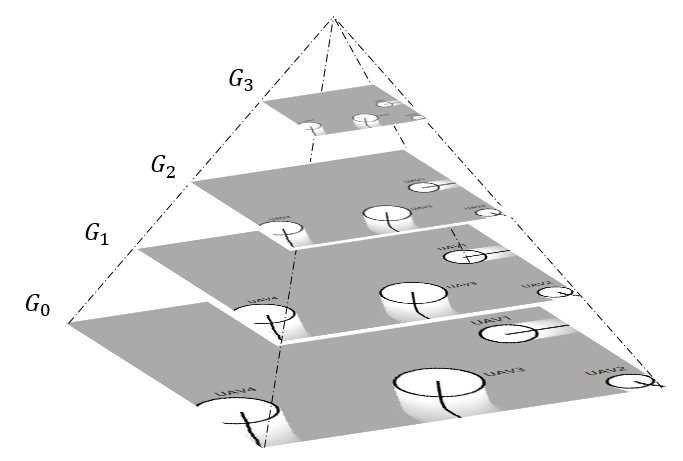
Inspired by its successful use in computer vision, a map pyramid is constructed for a better understanding of the mission area. The map pyramid is a multi-scale representation in maps, which is an effective structure with simple concepts to interpret maps with multiple resolutions for better understanding of the task area, avoiding falling into local points and enhancing robustness. The best-know hierarchical structures are the Gaussian[文献40] and Laplacian pyramids[文献41]. The pyramid model is one of the most intuitive multiscale descriptions of the signal and generally consists of two steps: first, the map is smoothed by a Gaussian filter, and then the smoothed map is sampled or interpolated to obtain a sequence of scaled-down or scaled-up maps, as shown in **Figure 3**. Each level of map in the sequence is the result of sampling every other row and column down after Gaussian filtering of the previous level of map. That is,



where,  is the map of the K-layer Gaussian pyramid;  is the original map as the lower layer of the Gaussian pyramid;  is a  window function with low-pass property.  is the Gaussian density distribution function which satisfies the constraints: normalization, symmetry, parity term and other contribution terms, then the window function  can be expressed as follows:



Thus,, , ...,  forms the Gaussian pyramid of uncertainty map.



**Figure 3.** Illustration of a 4 layers uncertainty gird map pyramid

2.3 Constraints of Cooperative Planning Problem

The constraints of multi-UAV flight path planning mainly include dynamic constraints, collision avoidance constraints, threat avoidance constraints, and communication constraints which are described as follows.

2.3.1 Dynamic constraint

When carrying out a search mission, the fixed-wing UAV usually moves on a horizontal plane and the motion model can be simplified to a particle’s motion on a two-dimensional plane without considering the size of the UAV.





where  is the position of fixed-wing UAV in flight profile,  is the heading angle. For fixed-wing UAV, the linear acceleration  is restricted by engine performance, and its speed  is affected by air:



Turning angular velocity is given by  where the turning radius  should be bigger than the minimum turning radius .



2.3.2 Collision avoidance constraints

Considering the flight safety, the distance  between UAVs should be bigger the minimum distance to avoid colliding:



2.3.3 Threat constraint

In general, the mission area contains numerous threats, which have a negative impact on the UAVs’ mission execution. Therefore, it is necessary for UAVs to avoid threats while carrying out missions. The distance  between the UAV and the threat center should be bigger than the threat radius , which can be expressed as:



3. DACMP for Cooperative search-track mission planning

Suppose there are N UAVs performing cooperative search-tracking tasks, and each UAV corresponds to a particle swarm that consists of M particles representing possible solutions of the optimal state vector. Each particle can be regarded as a search individual with flight speed and direction in an n-dimensional search space, and the current position of the particle is a candidate solution to the corresponding optimization problem. The value of the objective function at each particle state is evaluated by introducing the fitness function under the constraint set, which is the key to the algorithm. The flight process of the particles is equivalent to the individual search process. The particles explore the state space and find the optimal solution by referring to their previous best flight experience and the experience of other individuals in the swarm.

3.1. Objective Function

3.1.1. Search benefit function

When a UAV performs a search mission, the goal of the search mission is to reduce the uncertainty in the mission area to maximize the probability of detection of target. Therefore, UAVs tend to fly to the locations with high uncertainty. The bottom layer of the map pyramid only considers information about the current location of the particle and lacks knowledge of the whole map, which will lead the algorithm to enter a local optimum and repeat the search in a small area. For example, the local optimum may cause the UAV to enter the searched area, thus weakening the search performance of the UAV swarm. And the top layer of the map pyramid loses the detail information, which leads to low accuracy. Therefore, a bidirectional process as shown in Figure 4 is designed to solve this problem, which can be described as:



where and  are the state of the -th UAV and its neighbors, respectively.  is the expected value of next waypoint for this UAV.  is the balancing factor. is the bottom-up search value and  is the top-down search value.

|  |  |
| --- | --- |
|  |  |
| (**a**) | (**b**) |

Figure . The bidirectional process for search benefit: (**a**) bottom-up process; (**b**) top-down process.

Bottom-up search mechanism: To avoid the UAV from falling into the local optimum, we use the bottom-up search mechanism to represent the search benefits as shown in Figure 4a, which can be expressed as:



where  is the uncertainty about the potential target that exists on the region where the particle in the -th level of the map pyramid.  is the detection radius of UAV . A dubins path  is used to measure the distance from the particle to the UAV. Taking the 7-layer pyramid as an example, the seventh layer of the pyramid divides the map into 6 x 6 sub areas. The value of each grid represents the synthesis of the uncertainty of this sub area. Areas with high uncertainty should have higher search priority.

Top-down search mechanism: To improve the accuracy of the global metrics and increase the efficiency of the search, we introduced the top-down search mechanism using a Gaussian pyramid shown as Figure 4b, which is designed as follows: (P怎么算的缺乏解释)



As shown in Figure 5, the global indicator  represented by the center of the nearby area in a larger view.  is the angle among the position of UAV, candidate particle, and the global indicator . It makes the optimized waypoint more inclined to the direction of global indicator and guides the UAV to search in h the direction of the high uncertainty region, thus improving the mission search efficiency.

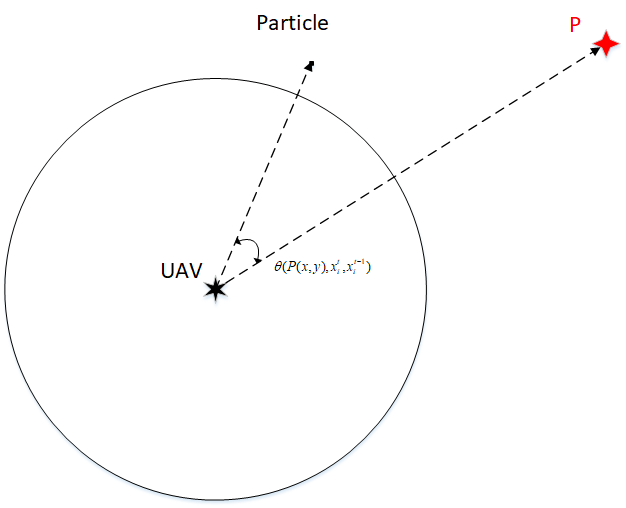


Figure . The usage of global indicator

3.1.2. Task Allocation

Text.

不论是在搜索与摧毁任务中还是在搜索监视任务中，无人机发现目标后，通常会分配某一架或多架无人机执行摧毁或监视任务。任务执行期间，该无人机其搜索对全局的贡献比较小。由于无人机从发现目标到摧毁目标的时间比较短，因此在任务分配时只会考虑目标与无人机间的距离以及无人机本身的任务状态。目标摧毁后，无人机又重新返回到搜索状态，整个无人机群重新回到最优搜索状态。但是在监视场景下，无人机需要一直保持对目标的追踪，这使得单架或某几架无人机在执行追踪任务后，无人机群整体的搜索能力是会一直保持在更低的水平的。而异构无人机的搜索与追踪能力各有差异，需要设计合理的任务分配机制，使得无人机群整体的始终保持最优的搜索能力同时维持对目标群的追踪。注意到不论是搜索还是追踪，都可以通过求取导引航迹点的方式引导无人机进行任务。我们将其他无人机的影响建模为排斥立场，将目标的影响建模为吸引力，则无人机的运动可以描述为无人机在势场内的运动。其中，力场公式如下：

其中U为合外力势能，为目标对当前无人机的吸引力场势能函数，为吸引力场势能函数。为了使得搜索能力更强的高速无人机执行搜索任务，追踪能力更强的低速无人机执行追踪任务，对于异构无人机而言，目标对低速无人机的吸引力要大于高速无人机对低俗无人机的排斥力排斥力与吸引力应当满足：

对于同构无人机而言，为了避免多架无人机同时追踪一个目标，导致无人机群的全局搜索能力降低，无人机的排斥力应当大于目标的吸引力。

3.2. Improvement of PSO Algorithm for Cooperative Misson Planning

Inspired by the foraging behavior of birds, PSO is a technique with many key advantages and has been widely used in path planning for mobile robot navigation[文献34-36], It has two important characteristics of swarm intelligence, namely cognition and social coherence which allow each particle of the population to search for solutions by following individual and group experiences, rather than using traditional evolutionary operators such as mutation and crossover[文献34]. Therefore, compared with other algorithms, The PSO algorithm has advantages in terms of computational efficiency, and the solution has stable convergence characteristics[文献37]. At the same time, it will not be greatly affected by the change of initial conditions and objective function, and can adapt to various environmental constructions with a small number of parameters[文献38].

To avoid early convergence to a local optimum and further improve the performance of the PSO, the algorithm is improved. First, the initial values of the control variables obey a normal distribution, traversing the allowed range. Second, according to the literature [19], inertia weight w, cognitive and social coefficients c1, c2 are introduced that decreases linearly with iteration. Finally, a random values is added to the velocity update formula as given by(速度公式还是位置公式再考虑一下)

公式

4. Experimental analysis

To give a thorough analyzation of the performance of DACMP algorithm performance described in this paper, a series of simulation experiments are set up. The simulation platform is a desktop computer equipped with 64-bit windows10 operating system, Inter(R) Core(TM) i5-8265u 1.6GHz CPU, and RAM 8G. The programming language used in the experiment following the C++14 standard, and the experimental results are analyzed in MATLAB. According to the information in section 3, the procedure flow of the simulation scene is shown in Fig. 7.

流程图

4.1. Experimental Parameter Setting

The mission area is 50km×50km inside which both UAVs and targets are moving. A 7-layer map pyramid with 100m×100m bottom resolution is used to model the mission area. To verify the performance of the algorithm to heterogeneous UAVs in multi-target search and tracking scenario, two different types of UAVs are adopted, states of which can be changed based on actual performance indicators. We use the same kinetics model of the UAV to simulate the movement of the target and a Wiener random process of acceleration is used. The maximum speed of target is lower than the slowest UAV to ensure tracking efficiency. The information of UAVs and targets are shown in Table 1.

To select the appropriate parameter values in the subsequent application of the DACMP algorithm, we analyzed the effect of parameter variations on the DACMP algorithm, i.e., the number of map layers L and the balance factor N, as shown in Figure 1. In addition, we perform 30 simulations for each parameter value to ensure reliability. Assuming that two type B UAVs search for 15 targets in the mission area, the initial positions are at (5, 5) km and (45, 45) km without considering the threats.我们认为搜索即追踪到，无人机接着搜索剩余目标。

As shown in Figs. 1 and 2, these two parameters are crucial to the performance of the search mission.在图1中，随着地图层数的增大，增加了无人机对全局的认识，从而提高搜索的效率，但是过大的地图层数可能会导致计算资源成本的增加，并且缺少了细节，导致无人机盲目向远处走去，而忽略了身边的风景，有点舍本逐末，舍近求远的感觉。以7层地图为例，4层时效果最好。

在图2中，当平衡因子为0.5时，搜索效率最高。

图1：地图层数，（a）前1000步的覆盖率和(b)目标数图（c）30次实验的覆盖率和(d)目标数

图2：平衡因子，（a）前1000步的覆盖率和(b)目标数图(c)30次实验的覆盖率和(d)目标数

**Table 1.** Parameter setup of UAVs and targets

|  |  |  |  |
| --- | --- | --- | --- |
| **Parameter** | **UAV** | | **Target** |
| Type | A | B | / |
| speed | 30~50m/s | 60-90m/s | 0-28m/s |
| Linear acceleration | ±0.4m/ | ±0.6m/ | ±0.4m/ |
| Maximum bank angle | 30° | 20° | / |
| Detection radius | 2km | 5km | / |

4.1.1. Subsubsection

Bulleted lists look like this:

* First bullet;
* Second bullet;
* Third bullet.

Numbered lists can be added as follows:

1. First item;
2. Second item;
3. Third item.

The text continues here.

4.2. Search Performance Analysis/Comparison with Search Model

To analyze the performance of DACMP algorithm in the search process, we conducted a set of experiments with the same scenario as in Section 4.1 and compared the performance with existing methods. The advantages of three methods are analyzed by comparing two metrics, the coverage of the region and the number of target searched. In addition, the median value is utilized to estimate their performance after 100 executions.

HAPF-ACO (Hybrid artificial potential field and ant colony optimization)[29]. It is based on Bayesian theory to estimate the motion state of the target, and combines the artificial potential field algorithm in the digital pheromone map to construct the target attraction field, threat repulsion field and repulsion field among the UAVs to ensure the completion of the search mission. In addition, if the coverage rate remains constant in some iterations, the ants move to the nearest unsearched grid, thus increasing the coverage rate of the domain and improving the global search capability. However,它只关注下一次迭代候选栅格的不确定度，而不是考虑带迫切搜索区域的不确定度，这会导致整个搜索任务陷入局部最优。

D2PIO (Dynamic discrete pigeon-inspired optimization)[参考文献], which focuses on improving the shortcomings of the standard PIO. By introducing global optima and center position detectors, the number of consecutive iterations without improvement is counted. If the pigeons are saturated, an external push is provided to propel them toward the unexplored space. Thus, the local optimum problem is avoided, and the search efficiency is improved. Although this strategy avoids the problem of local optimality of PIO, it still only focuses on the magnitude of uncertainty of a raster rather than considering the uncertainty of the whole region, which will cause the whole search process to fall into local optimality and cannot improve the efficiency of search task.

DACMP (Distributed autonomous cooperative mission planning algorithm). The DACMP algorithm based on distributed PSO algorithm combines bottom-up and top-down mechanisms with a same set of pyramids without additional computational overhead to better prevent UAV from falling into local optimization.(我们的算法不只考虑了当前候选栅格的不确定度，还考虑了栅格附近整个区域的不确定度，以及迫切待搜索区域的方向指引。考虑了当前搜索代价和长期搜索代价，并不一味地追求当前最优，而是追求长期最优，无人机就能选择更好的路径对区域进行搜索，从而提高了整体的搜索覆盖率。And 看看要不要改名字，放大一下优点)



**Figure 1.** This is a figure. Schemes follow the same formatting.

**Table 1.** This is a table. Tables should be placed in the main text near to the first time they are cited.

|  |  |  |
| --- | --- | --- |
| **Parameter** | **Title 2** | **Title 3** |
| entry 1 | data | data |
| entry 2 | data | data 1 |

The text continues here (Figure 2 and Table 2).

|  |  |
| --- | --- |
| C:\Users\martin\Downloads\testFigure.tif | C:\Users\martin\Downloads\testFigure.tif |
| (**a**) | (**b**) |

**Figure 2.** This is a figure. Schemes follow another format. If there are multiple panels, they should be listed as: (**a**) Description of what is contained in the first panel; (**b**) Description of what is contained in the second panel. Figures should be placed in the main text near to the first time they are cited.

**Table 2.** This is a table. Tables should be placed in the main text near to the first time they are cited.

|  |  |  |  |
| --- | --- | --- | --- |
| **Title 1** | **Title 2** | **Title 3** | **Title 4** |
| entry 1 \* | data | data | data |
| data | data | data |
| data | data | data |
| entry 2 | data | data | data |
| data | data | data |
| entry 3 | data | data | data |
| data | data | data |
| data | data | data |
| data | data | data |
| entry 4 | data | data | data |
| data | data | data |

\* Tables may have a footer.

4.3. Search-Track Performance Analysis/Mission Execution Analysis(跟踪改为监视)

4.3.1 case1: 3VS2 无障碍物 验证任务分配

两个目标隐藏在任务区域内，我们使用三架无人机进行目标的搜索与跟踪，以此来验证基于势场的任务分配的有效性。初始阶段，三家无人机从任务区域边缘进入，按照搜索策略进行区域搜索。第xxx步时无人机2探测到目标1。此时目标1对无人机2产生了吸引力场，粒子群受到吸引力长的作用而逐渐收敛到目标1上，从而使得无人机2向着目标1前进，达到追踪的效果。同时，无人机1也受到目标的吸引力作用，由于无人机1的速度小于无人机2，其搜索能力小于无人机2，更适合用于目标追踪，此时吸引力大于无人机2的排斥力，因此无人机的合力也指向目标，无人机在粒子群的引导下朝着目标前进。当无人机1到达目标附近后，无人机2受到无人机1的排斥力大于目标的吸引力，此时粒子群朝着远离无人机1与目标1的方向前进，进而让无人机2继续进行搜索任务，而无人机1则保持对目标1的追踪。由于无人机2的搜索能力要大于无人机1的搜索能力，经过这样的任务分配操作后，无人机群在维持目标追踪的同时进一步增强了搜索能力。注意到在无人机2发现并追踪目标时，无人机3也在目标1附近，但是其不受目标吸引力的干扰，继续进行搜索工作。这是因为同构无人机间的排斥力大于目标对无人机的吸引力，这样最近的一架无人机可以先锁定自身与目标的追踪关系，其他同构无人机则继续执行搜索任务，避免多架同构无人机对一个目标的纠缠导致的无人机群搜索能力的降低。该实验表明，本算法能够根据无人机能力，让无人机自发的进行搜索与追踪的任务切换，使得整个无人机群达到最佳的搜索与追踪状态。（这个图不太好，因为U3在往U1搜过的地方去，实际应该去右上角空白的地方）

|  |  |  |
| --- | --- | --- |
|  |  |  |
| (a) UAV2 is tracking target1 | (b) UAV1 is tracking target1 | (c) UAV2 is tracking target2 |

4.3.2 case2: 3V2 无障碍物 验证融合

（可以无实验，在case1中几句话说明）

一般发现目标后，通常的做法是采用单独的任务分配策略来指定某架无人机执行目标跟踪任务。这种策略通常只会考虑无人机与目标间的位置关系以及无人机固有的特性，而很难考虑各个无人机所在位置附近的区域搜索情况。我们的策略将搜索和追踪耦合在一起，能够更好的平衡搜索与追踪的关系，从而在保证目标追踪的同时能够以更好的状态进行区域搜索。在此同样使用3架无人机搜索两个目标。初始状态无人机群已经开始了一段搜索，导致有些区域已经被搜索过了。经过一段时间后，无人机2成功发现目标，此时无人机3也在目标附近。如果仅考虑无人机与目标的位置关系，此时无人机2因该去追踪目标，无人机3继续进行搜索。但此时无人机3附近的区域不确定度低，而无人机2附近的区域不确定度高。在未来一段时间内，无人机3的搜索收益显然不如无人机2。在此条件下，无人机3附近的不确定度势场要小于无人机2与目标合外力势场，而无人机2附近的不确定度势场要大于无人机3与目标合外力势场。使得无人机2朝着搜索收益大的方向前进，而无人机3则朝着目标前进。图二展示和融合策略和非融合策略下，搜索收益的表现，结果表明，本算法能够更好的引导无人机群完成搜索与追踪任务。

4.3.3 case3: 10VS6 有障碍物 复杂环境下系统表现

为了验证算法在复杂环境下的表现，我们设计了在有障碍物环境下，使用10架无人机去搜索并追踪6个目标的实验，其中UAV1-5为低速无人机，UAV6-10为高速无人机。为了体现异构无人机的搜索特性，我们将无人机的起始位置放置在任务区域两侧，而将目标放置在任务区域中央附近。Figure2表明了整个任务执行期间无人机和目标的运动轨迹。从Figure2(abcde)可以看到，由于高速无人机运动速度快，搜索能力强，目标2,3,4,5,1先后被高速无人机探测到并开始追踪，无人机群的探测能力有所下降。高速无人机探测到目标后，目标信息通过信息交互得方式共享给附近得低速无人机，目标附近的低速无人机开始受到目标吸引力场的作用开始向着目标移动。对比Figure2be可以看到，无人机1受到目标3得吸引而逐渐靠近目标。无人机1移动到目标3附近后，无人机7被无人机1的排斥力场所影响而解除对目标的追踪，转而继续进行区域搜索。过程中低速无人机取代了高速无人机对目标进行追踪，高速无人机取代了低速无人机对区域进行搜索。其余低速无人机2，3，4也同样得先后与高速无人机8，9，10完成任务转换，最终所有低速无人机都进行目标追踪，从而让无人机群在保持目标追踪得同时保留了无人机群最强得搜索能力。

|  |  |  |
| --- | --- | --- |
|  |  |  |
| 1. Target2 firstly tracked by UAV9 | 1. Target3 firstly tracked by UAV7 | 1. Target4 firstly tracked by UAV8 |
|  |  |  |
| 1. Target5 firstly tracked by UAV10 | 1. Target1 firstly tracked by UAV8 | 1. Target6 firstly tracked by UAV5 |

**Figure 2. The trajectorys of UAVs and targets when a target was tracked by UAV swarm**

轨迹图，覆盖率图，任务完成情况表格或者图

4.4. System scalability and adaptability analysis of DACMP

4.4.1 case4: 进入一架无人机 无人机数量动态条件

轨迹图，覆盖率图，搜索到的目标数量图 ，（是否还需要画一个被谁搜索到，又被谁追踪到的表格？）

4.4.2 case5: 退出一架无人机 无人机数量动态条件

轨迹图，覆盖率图，搜索到的目标数量图 ，（是否还需要画一个被谁搜索到，又被谁追踪到的表格？）

4.4.3 case6：进入/推出一个目标 目标数量动态条件

（可以没有，太多实验了）

5. Discussion

Authors should discuss the results and how they can be interpreted from the perspective of previous studies and of the working hypotheses. The findings and their implications should be discussed in the broadest context possible. Future research directions may also be highlighted.

6. Conclusions

This section is not mandatory but can be added to the manuscript if the discussion is unusually long or complex.

References

1. Ollero A, Kondak K. **10 years in the cooperation of unmanned aerial systems**. In: IEEE. pp. 5450-5451.

2. Du Y-C, Zhang M-X, Ling H-F, Zheng Y-J. **Evolutionary Planning of Multi-UAV Search for Missing Tourists**. *IEEE Access* 2019; 7:73480-73492.

3. Wang Y, Bai P, Liang X, Wang W, Zhang J, Fu Q. **Reconnaissance Mission Conducted by UAV Swarms Based on Distributed PSO Path Planning Algorithms**. *IEEE Access* 2019; 7:105086-105099.

4. Wu Y, Wu S, Hu X. **Multi-constrained cooperative path planning of multiple drones for persistent surveillance in urban environments**. *Complex & intelligent systems* 2021; 7(3):1633-1647.

5. Berger J, Happe J. **Co-evolutionary search path planning under constrained information-sharing for a cooperative unmanned aerial vehicle team**. In: IEEE. pp. 1-8.

6. Li C, Yang C. **Cooperative search of multiple robots with a distributed algorithm**. In. pp. 5630-5635.

7. Zhen Z, Xing D, Gao C. **Cooperative search-attack mission planning for multi-UAV based on intelligent self-organized algorithm**. *Aerospace Science and Technology* 2018; 76:402-411.

8. Sujit PB, Sousa JB. **Multi-UAV task allocation with communication faults**. In: IEEE. pp. 3724-3729.

9. Redwan Newaz AA, Jeong S, Lee H, Ryu H, Chong NY. **UAV-based multiple source localization and contour mapping of radiation fields**. *Robotics and autonomous systems* 2016; 85:12-25.

10. Shao S, Peng Y, He C, Du Y. **Efficient path planning for UAV formation via comprehensively improved particle swarm optimization**. *ISA transactions* 2020; 97:415-430.

11. Kumar S, Pandey KK, Muni MK, Parhi DR. **Path Planning of the Mobile Robot Using Fuzzified Advanced Ant Colony Optimization**. In: *Innovative Product Design and Intelligent Manufacturing Systems*. Edited by Deepak B, Parhi DRK, Jena PC. Singapore: Springer Singapore; 2020. pp. 1043-1052.

12. Wang Y, Hussein II. **Awareness coverage control over large scale domains with intermittent communications**. In: *2008 American Control Conference*; 2008. pp. 4370-4375.

13. Skoglar P, Orguner U, Törnqvist D, Gustafsson F. **Road Target Search and Tracking with Gimballed Vision Sensor on an Unmanned Aerial Vehicle**. 2012; 4(7):2076-2111.

14. Meng W, He Z, Su R, Yadav PK, Teo R, Xie L. **Decentralized Multi-UAV Flight Autonomy for Moving Convoys Search and Track**. *IEEE Transactions on Control Systems Technology* 2017; 25(4):1480-1487.

15. Cui S, Chen Y, Li X. **A Robust and Efficient UAV Path Planning Approach for Tracking Agile Targets in Complex Environments**. 2022; 10(10):931.

16. Niu X, Yuan X, Zhou Y, Fan H. **UAV track planning based on evolution algorithm in embedded system**. *Microprocessors and Microsystems* 2020; 75:103068.

17. Yang H, Bai X, Baoyin H. **Rapid generation of time-optimal trajectories for asteroid landing via convex optimization**. *Journal of guidance, control, and dynamics* 2017; 40(3):628-641.

18. Chai R, Savvaris A, Tsourdos A, Chai S, Xia Y. **Trajectory Optimization of Space Maneuver Vehicle Using a Hybrid Optimal Control Solver**. *IEEE transactions on cybernetics* 2019; 49(2):467-480.

19. Trummel KE, Weisinger JR. **The Complexity of the Optimal Searcher Path Problem**. *Operations research* 1986; 34(2):324-327.

20. Zhao Y, Zheng Z, Liu Y. **Survey on computational-intelligence-based UAV path planning**. *Knowledge-Based Systems* 2018; 158:54-64.

21. Roberge V, Tarbouchi M, Labonte G. **Fast Genetic Algorithm Path Planner for Fixed-Wing Military UAV Using GPU**. *IEEE transactions on aerospace and electronic systems* 2018; 54(5):2105-2117.

22. Liu Y, Zhang X, Guan X, Delahaye D. **Adaptive sensitivity decision based path planning algorithm for unmanned aerial vehicle with improved particle swarm optimization**. *Aerospace science and technology* 2016; 58:92-102.

23. Duan H, Zhao J, Deng Y, Shi Y, Ding X. **Dynamic Discrete Pigeon-Inspired Optimization for Multi-UAV Cooperative Search-Attack Mission Planning**. *IEEE Transactions on Aerospace and Electronic Systems* 2021; 57(1):706-720.

24. **<Optimal vs Heuristic Assignment of Cooperative Autonomous Unmanned Air Vehicles.pdf>**.

25. Shima T, Rasmussen SJ, Sparks AG, Passino KM. **Multiple task assignments for cooperating uninhabited aerial vehicles using genetic algorithms**. *Computers & operations research* 2006; 33(11):3252-3269.

26. Zhang Y-z, Hu B, Li J-W, Zhang J-D. **Heterogeneous multi-UAVs cooperative task assignment based on GSA-GA**. In: IEEE. pp. 423-426.

27. Zhen Z, Chen Y, Wen L, Han B. **An intelligent cooperative mission planning scheme of UAV swarm in uncertain dynamic environment**. *Aerospace Science and Technology* 2020; 100.

28. Zheng Y-J, Du Y-C, Sheng W-G, Ling H-F. **Collaborative Human–UAV Search and Rescue for Missing Tourists in Nature Reserves**. *INFORMS journal on applied analytics* 2019; 49(5):371-383.

29. Zhen Z, Chen Y, Wen L, Han B. **An intelligent cooperative mission planning scheme of UAV swarm in uncertain dynamic environment**. *Aerospace Science and Technology* 2020; 100:105826.