Task-driven rule-based algorithm with mode-switching for UAV swarms in bounded areas

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Abstract. The decision-making of UAV swarms under restricted environments is very important to exert the swarm effectiveness. On the basis of bio-inspired rule-based (Bio-RB) decision-making algorithms, this paper proposes a task-driven rule-based (Task-RB) decision-making algorithm. A mapping mechanism from behavioral rules to task modes and a probability-based mode-switching strategy are established for search and target attracting tasks. In order to improve the efficiency of performing tasks at regional boundaries, a boundary handling strategy based on the combination of path prediction and virtual agents is proposed. Taking search and target attracting tasks as examples, the Task-RB and Bio-RB algorithms are compared and tested. Simulation results demonstrate the effectiveness and adaptability of the proposed decision-making method to perform the above tasks in bounded areas.

Keywords: UAV Swarm, Adaptive Decision-Making, Task Mode Switching, Boundary Handling

1. INTRODUCTION

With the development of control technology and communication technology, the autonomous capability of unmanned aerial vehicles (UAVs) is gradually improving. UAV swarms gradually develop in the future direction of semi-autonomous or fully autonomous [1]. Swarm decision-making methods are usually divided into two types: centralized decision-making and distributed decision-making [2]. The centralized decision-making method is more common, but the robustness of this method is poor. Once the central node fails, the entire UAV swarm system will collapse. In recent years, distributed decision-making has become a research hotspot in the field of UAV swarms due to its advantages of high reliability, strong robustness, and low communication pressure. The majority of classical distributed swarm decision-making methods stem from the behavior of biological groups in nature. Individuals in UAV swarms can maintain a coordinated and unified movement and respond quickly and consistently to external environmental stimuli. Even if the individual intelligence is low, a higher intelligence can emerge at the group level through simple information exchange. Inspired by the self-organizing behavior of natural organisms, UAV swarm technology began to develop rapidly, with UAV swarms exhibiting ordered behavior through artificially set behavioral rules for them to use or follow. Reynold [3] established the Boids model, in which each agent interacts with other individuals locally and achieves a certain degree of autonomous cooperation with three most basic rules. However, this method has poor scalability and environmental adaptability. Vicsek et al. [4] proposed the Vicsek model from the perspective of statistical mechanics. By modifying parameters, such as swarm density and noise intensity, they quantitatively analyzed the mathematical model inspired by biology. Pearce et al. [5] proposed a mathematical model that uses projection to simulate the information transfer in bird flocks. The model uses a small number of parameters to control the density of bird flocks and then simulates the flight patterns of various bird flocks. It provides a new idea for swarm perception and interaction. Aiming at the perception, computing, and planning capabilities required by the swarm system to complete the given task, Price et al. [6] updated and supplemented the classic behavior rules and proposed ten self-organizing rules. The objective function related to the task determines the appropriate combination of rules. Yang [7] proposed a self-organizing control algorithm for robots swarm performing target search and capture tasks. The algorithm is not easy to fall into local optimum and has high computational efficiency.

However, UAV swarms usually perform tasks in a completely ideal environment, and various types of evasion issues need to be considered to ensure their own safety. At present, there are global planning methods, such as heuristic search methods [8][9], graph-based methods [10][11], and others, for dealing with collision avoidance among UAV individuals and environmental obstacle avoidance. However, these methods have poor adaptability and low planning efficiency in highly dynamic and uncertain environments. In contrast, the local planning methods can be more flexible and achieve dynamic perception avoidance. Fakoor et al. [12] established a fuzzy artificial potential field through local data to realize real-time path planning, which solved the problem of UAV collision avoidance control in unknown

environments. Viragh et al. [13] proposed a virtual force-based method to achieve the avoidance effect by converting the original potential field into a repulsive force potential field between individuals. However, the current research on collision avoidance mainly focuses on collision avoidance between individuals and collision avoidance with obstacles. When the mission to be performed by the UAV swarm is limited to a bounded area, how the UAV swarms act when where reach the boundary becomes a key factor affecting the mission effectiveness. Kaiser et al. [14] proposed a prediction-based method to make UAVs turn maneuverable. Gábor et al. [15] proposed a virtual agent-based handling method to solve the boundary problem suitable for rotor UAV swarm. This kind of research dealing with the boundary problem can improve the task efficiency of UAV swarms in bounded regions.

After the UAV swarm enters the mission area, it will face a variety of tasks. These tasks are often unknown in advance, so it is necessary to respond quickly to the information perceived by UAV swarms. This requires the introduction of event-triggered mechanisms in decision-making. Dimarogonas et al. [16] introduced the continuous event-triggered control method into the multi-agent system. By collecting the real-time state information of the system to drive the controller of a single agent, the update of the multi-agent system is finally realized. However, this kind of continuous event trigger mechanism requires continuous measurement of the system state, so the requirements for hardware conditions are very high. Zhang et al. [17] proposed an event-triggered approach based on adaptive control to resolve the uncertainty in networked control systems. At the same time, the event triggering parameters can be adjusted adaptively. In many task scenarios, the swarm decision-making method based on the event-triggered mechanism can show better task performance than the time-triggered mechanism.

For the search and target attraction tasks in bounded areas, this paper proposes an adaptive decision-making method for UAV swarms. Through testing, the simulation results demonstrate the effectiveness and adaptability of the proposed swarm decision-making algorithm. The innovations of this paper mainly include: (1) For the UAV swarm decision-making method, a behavior mode switching mechanism based on probability is introduced. Compared with the method of triggering task switching based on threshold. This method does not need to determine the selection of threshold and has certain progressiveness. (2) For the less-researched boundary processing problem, this paper proposes a combination of prediction mechanism and boundary handling method combined with the concept of virtual agents. This strategy makes the UAV have greater randomness after encountering the boundary, and indirectly affects the coverage of the UAV group on the whole area, which is more reasonable than the traditional method.

The rest of this paper is structured as follows. Section 2 details the bio-inspired rule-based decision-making algorithm. Section 3 introduces the adaptive distributed decision-making algorithm including the mapping relationship between behavior rules and behavior modes. The simulation results are presented in Section 4. The last section concludes this paper and identifies future work.

2. BIO-INSPIRED RULE-BASED DECISION-MAKING ALGORITHM

Behavior rules are the most basic behaviors that UAVs can accomplish, and the overlay of different rules can allow UAVs to emerge with complex behavioral patterns. This is the classic bio-inspired rule-based (Bio-RB) decision-making algorithm. In this study, we modified and added additional rules to the classic Boids model to provide UAV swarms with capabilities relevant to their tasks. These behaviors include alignment, cohesion, separation, and target attraction, with the final output of a single rule being the desired velocity of the UAV. In this paper, the set of UAV swarm is defined as $U = \{U_{1,\dots,}U_n\}$, the ground stationary target set is $T = \{T_{1,\dots,}T_m\}$. This allows UAVs to respond inconsistently to other individuals and maintain a certain distance from them, facilitating the expansion of the UAV swarm. The perception and information interaction between UAVs are simplified into a two-way communication model. Since all UAVs have the same capabilities, the detection range of the UAV sensor is uniformly defined as Sr, and friendly UAVs within the sensing range of U_i are called neighbors. For the UAV U_i, all the individuals it perceives together form a set $\widetilde{U}_i$. The calculation formula is as follows, where p_i^U represents the position of U_i; p_k^U and v_k^U are the position and velocity of the kth neighbor, respectively. The function *dist* represents the Euclidean distance between two UAVs.

$$\widetilde{U}_i = \left\{U_k \in U | dist\left(p_i^U, p_k^U\right) < S_r\right\} \quad (1)$$

It should be noted that the definition of the set of neighbors is slightly different under different behavior rules, and the influence coefficients are r_1, r_2 and r_3. The relevant meanings and mathematical definitions of behavior rules will be described in detail below.

2.1. Alignment Rule

The alignment rule keeps the velocity of a UAV and its neighbors in the same direction. For this rule, a proportional coefficient r_1 related to the rule is defined, and the neighbor individual set effectively corresponding to the rule is updated by (2), $|\cdot|$ represents the cardinality of the set, and r_3 is the ratio related to the separation rule which will be introduced later.

$$\widetilde{U}_{i.R1} = \left\{U_k \in U | r_3 * Sr < dist\left(p_i^U, p_k^U\right) < r_1 * Sr\right\} \quad (2)$$

$$v_{i,R1} = \left(\sum_{k=1}^{|\widetilde{U}_{i.R1}|} v_k^U / dist\left(p_i^U, p_k^U\right)\right) / |\widetilde{U}_{i.R1}| \quad (3)$$

2.2. Cohesion Rule

In the cohesion rule, the relevant scale factor r_2 is added to the definition of the original neighbors, and the updated neighbors are represented as the set $\widetilde{U}_{i.R2}$. The

calculation formula of the neighbor individual set and the rule is as follows. $v_{R2}$is the velocity output by this rule.

$$\widetilde{U}_{i.R2} = \{U_k \in U | r_1 * Sr < dist(p_i^U, p_k^U) < r_2 * Sr\} \quad (4)$$

$$v_{i,R2} = \left(\sum_{k=1}^{|\widetilde{U}_{i.R2}|}(p_k^U - p_i^U)(dist(p_i^U, p_k^U) - r_1 * Sr)\right)/|\widetilde{U}_{i.R2}| \quad (5)$$

2.3. Separation Rule

Defining r_3 as the correlation scale factor of the separation rule, the set of neighbors $\widetilde{U}_{i.R3}$ and the rule is calculated as follows. In some specific search tasks, the separation rule can achieve fast search coverage of unknown areas by UAV swarms.

$$\widetilde{U}_{i.R3} = \{U_k \in U | dist(p_i^U, p_k^U) < r_3 * Sr\} \quad (6)$$

$$v_{i,R3} = \left(\sum_{k=1}^{|\widetilde{U}_{i.R3}|}(p_k^U - p_i^U)(dist(p_i^U, p_k^U) - r_3 * Sr)\right)/|\widetilde{U}_{i.R3}| \quad (7)$$

It should be noted that the boundary handling mode introduced in Section 3.2.3 introduces the concept of virtual agents, which in this study refers specifically to virtual UAVs. The separation rule is equally valid in this mode, in addition to applying to collision avoidance between individuals within the group. Therefore, when U_i is in boundary handling mode, the boundary virtual UAV individual it perceives in this mode is defined to be V. At this time, the UAV i that needs to perform boundary handling will only consider the interaction with the virtual UAV V, which will be described in detail in Section 3.2.3.

2.4. Target Attraction Rule

This rule enables the UAV to approach the target after sensing it and thus perform a target-attracting task. For an enemy target within the detection range of the UAV i, it is defined as a set $\tilde{T}_i$, which is calculated as follows. p_k^T denotes the position of target k and v_{R4} is the velocity output by this rule.

$$\tilde{T}_i = \{T_k \in T | dist(p_i^U, p_k^T) < Sr\} \quad (8)$$

$$v_{i,R4} = \left(\sum_{k=1}^{|\tilde{T}_i|}(p_k^T - p_i^U)\right)/|\tilde{T}_i| \quad (9)$$

This section describes the bio-inspired rule-based decision-making model for UAVs. A variety of swarm behaviors can be achieved through the weighting of these rules.

3. ADAPTIVE DISTRIBUTED DECISION-MAKING ALGORITHM

An overview of the adaptive decision-making process applicable to UAV swarms is given in this section. Subsequently, the task-driven rule-based (Task-RB) decision-making algorithm will be introduced in detail.

3.1. Framework of the Task-RB Algorithm

In this study, the UAV swarm is primarily tasked with search and target attracting. If a UAV reaches the boundary during this period, it needs to make maneuvering turn to keep itself in the delimited area and then continue the subsequent task. Therefore, task modes are classified as the search mode, the target attracting mode, and the boundary handling mode. The flow chart of the proposed adaptive distributed decision-making algorithm with probabilistic task switching is shown in **Fig 1**. First, the positions and velocities of all individuals in the UAV swarm are initialized. Then, the friendly individuals and perceived ground targets in the domain of each UAV are determined. The trajectory of the UAV is then predicted to determine whether the condition to switch to boundary handling mode is triggered. If the condition is satisfied, the task is switched so that the UAV completes the boundary handling and autonomous turning process. If it is not satisfied, the probability of switching to the target attracting mode is calculated based on whether a ground target is detected. Finally, the two task behaviors are selected according to the probability of switching tasks. So far, the current round of decision-making is completed. According to the decision frequency set by the algorithm, the neighborhood information needs to be re-determined in the next round of decision-making.

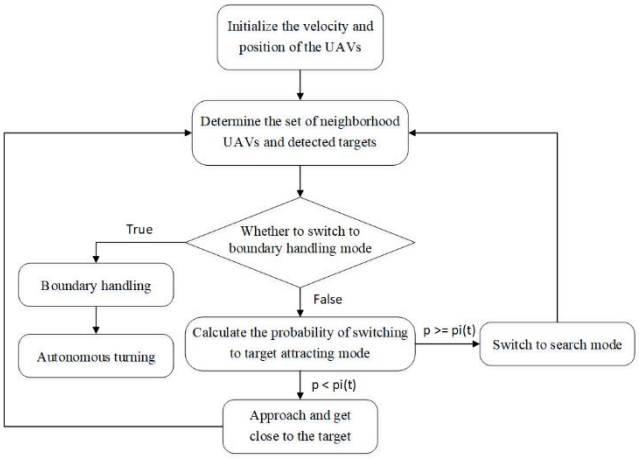


Fig. 1 The flow chart of the proposed Task-RB algorithm.

3.2. Behavior Mode

The task behavior mode of the UAV is based on the behavior rule set and is controlled by the task controller. In this paper, we mainly consider the search task and the target attracting task, thus corresponding to two task modes (i.e., the search mode and the target attracting mode). In addition, for distributed adaptive decision-making in bounded areas, a boundary handling model based on a prediction mechanism is proposed, which is proven to be effective not only for individual UAV but also for UAV swarms. The three behavior modes are described in detail below. It should be noted that different modes correspond to different combinations of behavior rules. When multiple rules work, we also set different weights for each rule. This paper represents the weights as $w_i (i = 1, 2, 3, 4)$ in the order of introduction in Section 2. No matter in any task behavior mode, it needs to satisfy $\sum_{i=1}^{4} w_i = 1$.

3.2.1. Search Mode

The search mode is similar to the classic Couzin model. A relatively stable two-dimensional swarm formation is formed by using the speed and position difference between a UAV and its neighbors. The interaction of the UAV is constrained by a coefficient related to the perception radius in the rules. A neighbor N_k have an attractive effect on the current UAV U_i, which avoids the swarm from being too dispersed to a certain extent and facilitates the formation of a tight formation. It indirectly affects the orderliness of the UAV swarm. Individuals located in the attraction zone influence the speed of the local UAV and drive the mutually sensed UAVs to fly in an orderly formation. The UAVs located in the orientation zone influence the speed of the local UAV and drive the mutually sensed UAVs to fly in an orderly formation. Neighbors distributed in the repulsion zone have a repulsive effect on the native UAV, causing the two UAVs to move away from each other and thus avoiding collisions between different UAVs during the gathering process [18].

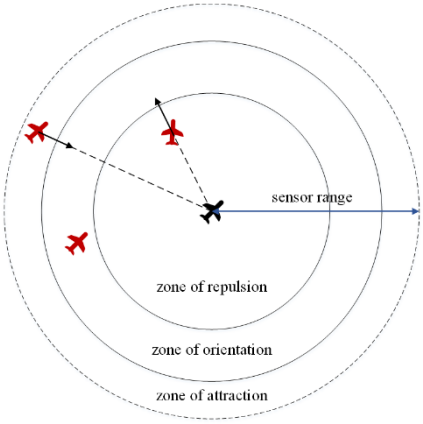


Fig. 2 Illustration of search mode area division

As can be seen from **Fig 2**, the boundary of the attraction zone corresponds to the detection radius of the sensor. According to the introduction in Section 2.1, there are mainly two states when the UAV is in the search mode. Namely, no target is found without reaching the boundary or the target has been found but not switched to target attracting mode, so only the first three rules are valid in this mode, i.e., the velocity when U_i is in search mode is defined as (10).

$$v_i^s = w_1^s \cdot v_{i,R1} + w_2^s \cdot v_{i,R2} + w_3^s \cdot v_{i,R3}\ (i = 1,2,\dots,n) \quad (10)$$

The weight of the behavior rules is set to $w_1^s = 1/3$, $w_2^s = 1/3$, $w_3^s = 1/3$. UAVs will search in relatively orderly formations while maintaining inter-aircraft communication. In the search mode, if the cohesion rule and separation rule are ignored for the purpose of improving the coverage rate, and the coverage rate is exchanged for the orderliness, it is contrary to the concept of "swarm".

3.2.2. Target Attracting Mode

A probability-based event-triggered mechanism enables the UAV swarm to better complete multi-target attracting tasks. In this way, the task overlap of all UAVs can be reduced on the premise of ensuring the search coverage. Specifically, it can be interpreted as not wasting limited search resources on low-value targets. This task is also performed within bounded areas. A number of ground stationary targets are randomly set in the area. In this mode, if successfully switched to the target attracting mode, a gravitational vector close to the target will be generated.

Inspired by Bonabeau et al. [19], they believed that the self-organization and division of labor in social insects can be explained and illustrated by a response threshold model. They established a set of task assignment models based on response thresholds to quantify external stimuli. Finally, a mathematical model is used to describe the possibility of responding to the stimulus. In this task assignment model, the response threshold θ is the unit of stimulus intensity, which determines the current individual's response to the stimulus intensity S and the tendency to complete the task. The response function $T_\theta(S)$ is used to express the probability of completing the task and is defined as (11).

$$T_\theta = S^n/(S^n + \theta^n) \quad (11)$$

From this function, it can be seen that the value of n determines the degree of change of the response function, and the relationship between S and θ affects the probability of participating in the task. In the research of this paper, it is obviously unrealistic and inefficient to allow the UAV swarm to cover the entire area and then get close to the target. The focus of the research is to cover the entire limited search area to the greatest extent, and to maximize the target attracting time to ensure that all targets are attracted. Therefore, we designed an adaptive task-switching model based on task stimulus intensity and response threshold.The stimulus intensity associated with the target is updated as (12).

$$S(t+1) = \begin{cases} 1 & \tilde{T}_i \neq \emptyset \\ 0 & \tilde{T}_i = \emptyset \end{cases} \quad (12)$$

Assuming that the UAV detects the existence of a ground target, the stimulus intensity is set to 1, otherwise, it is 0. The task switching probability is described as (13).

$$P_i(t) = S_i^2/(S_i^2 + \alpha \cdot \theta^2) * \left(1 - e^{-\delta/dist(p_i^U, p_k^T)}\right) \quad (13)$$

This paper makes some improvements on the basis of the original response function. Among them, θ represents the number of friendly neighbors perceived by the current UAV, α is the coefficient to control the influence of θ, and δ represents the own combat capability required by the target. We take into account whether the target is found and the number of UAVs that perceive the target at the same time. The last term of the formula forces the UAV closest to the target to switch to the target attracting mode with a higher probability. The switching probability is also affected by the target. The greater the demand, the higher the probability of task switching, which means that the number of UAVs assigned to this ground target is more macroscopically. When the UAV U_i is in target attracting mode, the velocity is defined as (14).

$$v_i^t = w_4^t \cdot v_{i,R4}\ (i = 1,2,\dots,n) \quad (14)$$

Where $w_4^t = 1$, the weights of other rules are set to 0. It should be noted that the decision frequency is given in the algorithm, and the UAVs are independent of each other and make distributed decisions.

3.2.3. Boundary Handling Mode

Most of the classical swarm models focus on the internal movement mechanism of individuals and the process of information processing and transformation. These models also tend to manifest only in unbounded or periodic spaces. Therefore, for specific tasks in special environments, there are still functions that need to be improved. In a bounded area, the movement of the UAV needs to be constrained to keep it within our observable range. For such problems, the artificial potential field method assumes that the individual UAV moves under a virtual force field, which derives another processing mechanism based on virtual agents [14]. The virtual agent flies into a given bounded space at a certain speed and relies on the corresponding behavior rules to achieve the effect of staying away from the boundary when the collision avoidance priority is high. In this paper, a path prediction mechanism is introduced to improve the adaptive decision-making ability of the UAV swarm and the ability to complete the given task. When making a decision, the UAV will predict the position along with its current heading for 50 simulation steps in the future. The formula is as follows.

$$\varepsilon = \begin{cases} 1 & \left|p_i^U + \vec{d}\right| > \left|\overrightarrow{d_b}\right| \; or \; \left|p_i^U\right| > \left|\overrightarrow{d_b}\right| \\ 0 & \left|p_i^U + \vec{d}\right| \le \left|\overrightarrow{d_b}\right| \end{cases} \tag{15}$$

$\vec{d}$ denotes the position at the current UAV position after flying 50 steps along this moment toward the direction, and $\overrightarrow{d_b}$ denotes the region boundary. Although the model is based on a prediction mechanism, we have supplemented the decision condition in the formula. If the UAV exceeds the boundary, it will drive back to the predetermined bounded area. When the trigger condition is satisfied, the mode switching signal ε is set to 1, otherwise it is 0. This paper draws on the concept of virtual agent and realizes the idea of complex behavior based on simple rules. First, draw a vertical line from the UAV's current position to its nearest border. Then find a virtual agent that is located in the local repulsion zone on the vertical line and has a distance of d_V from itself. Finally, interact with the virtual agent and trigger the separation rule to ensure that the UAV is always located in the bounded area. If the UAV is outside the boundary, it will trigger the cohesion rule to re-enter the area.. Therefore, the velocity when the UAV U_i is in boundary handling mode is defined as (16).

$$v_i^b = w_3^b \cdot v_{i,R3} \; (i = 1,2,\dots,n) \tag{16}$$

Where $w_3^b = 1$, $v_{R3} = \left(p^V - p_i^U\right)(d_V - r_3 * Sr)$.

The application of this boundary handling method has a significant impact on the improvement of coverage and the ability to find stationary targets on the ground. Changes in the number of predicted steps will affect when the mode switch is triggered. If the parameter is too small, it will be too close to the boundary due to the late switching, so that the UAV tends to fly along the edge of the boundary. If this parameter is too large, the area on the edge of the border will not be effectively covered when the UAV makes a turning maneuver. This affects the search task to a certain extent. However, through multiple simulations, we can obtain the parameter value that is close to the best effect. Furthermore, we found that a single UAV would fly along the edge of the border to some extent after triggering this mode when there is no target. This is disadvantageous for performing search tasks in unknown bounded areas. However, with the increase in the number of UAVs, this situation has improved significantly. Since safety is a priority over everything else, neighbors have an additional rule-binding effect on UAVs that switch to this mode. This will lead to a large amount of change in the velocity orientation obtained by the current UAV decision. This amount of change leads to the change of the local state, which further affects the surrounding individuals in the subsequent decision-making, and then a good boundary handling effect emerges. For a sub-group of UAVs, switching the outer UAV to the boundary handling task mode will more intuitively affect the behavior and steering of the inner individual. This shortens the search path length of the inner UAV to a certain extent, making the swarm perform the coverage search task better and more efficiently.

4. SIMULATION RESULTS

Numerical simulations are performed in the multi-agent aircraft environment (MAE) [20]. This environment is suitable for small fixed-wing UAVs. It simplifies the dynamic model of the UAV to a two-dimensional plane and generates the control amount of the UAV through the Total Energy Control System (TECS) control of the outer loop, L1 control and the PID control of the inner loop. Therefore, it is closer to the real situation and has higher simulation precision and reliability.

4.1. Simulation Scene Settings

In the execution of area search and target attracting tasks, parameters settings of task scenarios are shown in **Table 1**. Taking the center point of the area as the origin, the initial position of each UAV is a random point in the small square area of $x, y \in [3.0,3.5]$. The initial speed is a random number in the range of $v_x, v_y \in [0, -0.01]$, pointing to the third quadrant.

Table. 1 Parameters settings of task scenarios.

Parameter	Value	Parameter	Value
Number of UAVs n	20	Initial position of UAVs p_i^U	$x, y \in [3.0,3.5]$
Detection radius Sr	0.6km	Initial velocity of UAVs v	$v_x, v_y \in [0, -0.01]$
Rule parameters r_1, r_2, r_3	0.9, 1.0, 0.8	Number of targets m	0, 4, 8
Boundary range $L_x \times L_y$	8km×8km	Mode switch parameters α	0.5

In addition, this paper chooses the Price's behavioral rule model [6] to compare with the method in this paper. Considering the task requirements, we use the genetic algorithm to optimize the weights of alignment, cohesion, separation and weighted target attraction. Finally, we choose the weight close to it as the final preset parameter. The weight is [0.2,0.05,0.45,0.3].

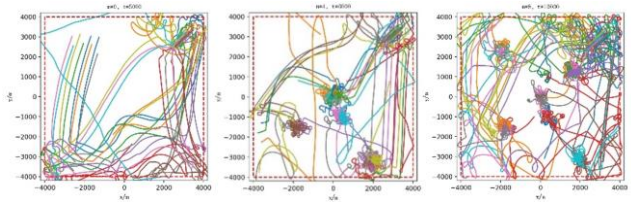
4.2. Search Task

For the regional search task in the bounded space, the proposed Task-RB algorithm and the decision-making model based on the weighted combination of rules are used to compare. Three sets of examples are set to test the effect of the algorithms.

In the case that the parameters of other mission scenarios are completely consistent, 10 tests are performed under each calculation example, and a set of test results is selected as the search track map. The trajectory generated by the Bio-RB algorithm and the proposed Task-RB algorithm are shown in **Fig 3** and **Fig 4** respectively. Due to the setting of the ground target, the coverage growth rate slows down, so it is intercepted to the first 5000, 6000, and 10000 steps of the simulation, respectively. Different colors represent different UAVs, and the red dotted box represents the delineated area boundary. The dense points in the track in the figure represent that the UAV finds the target and conducts surveillance.

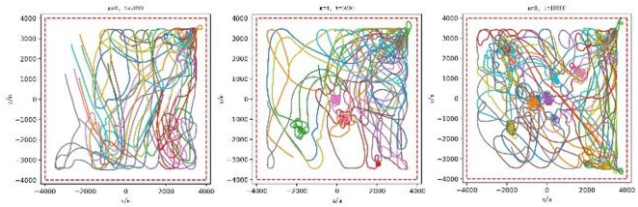
In order to more intuitively reflect the difference between the two methods, the regional search coverage under different calculation cases is compared, and the average value of multiple sets of test results is plotted, as shown in **Fig 5**. As can be seen from the figure, in the case of no target, the proposed Task-RB algorithm is significantly better than the Bio-RB algorithm. Combined with the analysis of the trajectory graph, it can be seen that the boundary handling method based on the prediction mechanism proposed in this paper is effective. This method can shorten the worthless search path of the UAV swarm to a certain extent, and make the effective search time account for a higher proportion, thereby reducing the waste of additional resources, which is of great significance for the search task in the actual environment.

It can be seen from these figures that the proposed Task-RB algorithm performs slightly better than the



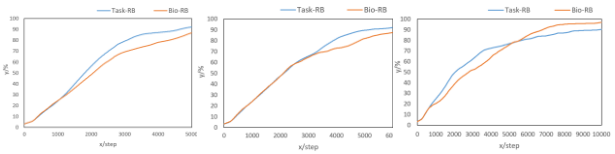
(a) $m = 0$ **(b)** $m = 4$ **(c)** $m = 8$

Fig. 3 Trajectory of the UAV swarms based on Bio-RB.



(a) $m = 0$ **(b)** $m = 4$ **(c)** $m = 8$

Fig. 4 **T**rajectory of the UAV swarms based on Task-RB.



(a) $m = 0$ **(b)** $m = 4$ **(c)** $m = 8$

Fig. 5 Coverage comparison of test instances with different number of targets.

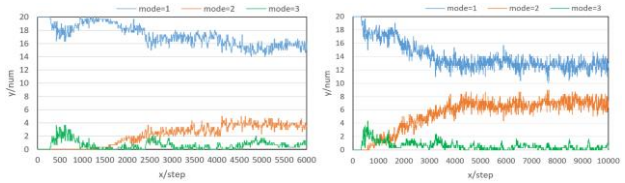
algorithm when the target is sparse, and the coverage is improved more significantly when the target is dense. This is because the method allocates resources reasonably to several targets, and the remaining UAVs continue to perform search tasks without wasting additional resources. The Bio-RB algorithm makes the number of UAVs monitoring the target slightly redundant, resulting in fewer UAVs continuing to perform search tasks, so the coverage growth rate is extremely slow. The coverage has just reached 90% in the simulation test of nearly 10,000 steps. To sum up, as the number of targets increases, the disadvantages of the Bio-RB algorithm gradually emerge, and it is impossible to achieve long-term monitoring with reasonable resource allocation.

4.3. Target Attraction Task

The comparison of decision-making algorithms for target-attracting tasks will start with effectiveness, because the ultimate purpose of search coverage is to serve the discovery, reconnaissance and strike of targets, so the completion of the task is the main evaluation index to measure the pros and cons of the algorithm. Here, the number of targets is also set to 4 and 8 to test the two algorithms respectively.

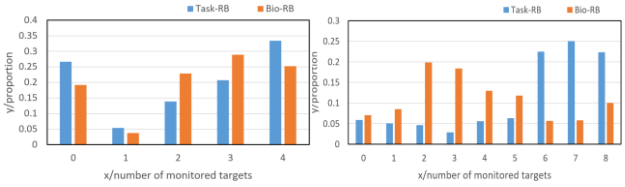
Define the search mode, target attracting mode and boundary handling mode under the mode switching method as mode1, mode2, and mode3, respectively. In the case of sparse targets, the number of UAVs that select different mission modes in each step of the mode-switching method is counted, as shown in **Fig 6(a)**. The horizontal axis in the figure represents the number of simulation steps, and the vertical axis represents the number of UAVs in different modes under a certain number of simulation steps. When the number of targets is 4, the average 1200th move finds and gets close to the first target. After about 4000 steps, the number of UAVs responsible for target attracting stabilized at 4. The number of drones in search mode is always maintained at 14 and above. At this time, it can be achieved that the efficient search for other areas can be maintained while getting close to all the targets.

The results of mode selection when there are more targets are shown in **Fig. 6(b)**, where the number of UAVs with the status of target attracting mode saturates after 4000 steps on average, implying that the target attracting task is more effective at this time, and the targets that have been detected are followed more completely. It should be noted that this does not mean that the targets were all detected and monitored. Therefore, we use the ratio of the number of different targets being followed to the total simulation time as one of the evaluation metrics.



(a) $m = 4$ **(b) $m = 8$**

Fig. 6 Mode selection results for UAVs.



(a) $m = 4$ **(b) $m = 8$**

Fig. 7 Comparison of the effect of the target-attracting task.

In **Fig 7**, the horizontal axis represents the number of targets, and the vertical axis represents the proportion of the time that different numbers of targets are monitored in the whole simulation process when the total number of targets is given. In the sparse target environment, the proposed Task-RB algorithm monitors all targets nearly 33.4% of the time. Although the Bio-RB algorithm successfully finds and monitors all targets, there is a phenomenon of target loss in the process, so there is only a 25.3% full monitoring rate. The proposed Task-RB algorithm has a 32% improvement compared to Bio-RB algorithm, and the detailed data are listed in **Table 2**.

When the number of targets is large, the advantage of the proposed Task-RB algorithm is more significant, 22.3% of the time is effectively monitored for all targets, and the phenomenon of target loss is very small. Multiple simulation results show that the effective monitoring time for more than 3/4 of the total number of targets accounts for nearly 70%, and there are still surplus UAVs to continue to perform search tasks to ensure coverage of other areas. In this example, the disadvantage of the Bio-RB algorithm is obvious, the effective full monitoring time only accounts for 10.1%, and only close to half of the targets are effectively followed most of the time. Since this method is prone to assigning an excessively redundant number of UAVs to each target, the number of UAVs that continue to search is small. However, due to the existence of other rules, the phenomenon of target loss also occurs from time to time, so the effect of target attracting is general.

Table. 2 The percentage of time the target is attracted under different methods.

(a) $m = 4$

	m=0	**m=1**	**m=2**	**m=3**	**m=4**
Bio-RB	0.192	0.037	0.229	0.289	0.253
Task-RB	0.267	0.053	0.138	0.207	**0.334**

(b) $m = 8$

	m=0	**m=1**	**m=2**	**m=3**	**m=4**
Bio-RB	0.070	0.085	0.198	0.184	0.129
Task-RB	0.059	0.051	0.046	0.029	0.056
	m=5	**m=6**	**m=7**	**m=8**	
Bio-RB	0.118	0.056	0.058	0.101	
Task-RB	0.063	**0.225**	**0.251**	**0.223**	

5. CONCLUSION

For UAV swarm tasks, most decision-making algorithms do not consider the bounded area constraints and do not have a clear task switching mechanism. Aiming at these problems, this paper proposes the Task-RB algorithm which enables UAV swarms to make adaptive decisions and complete the given tasks in bounded areas.

First, this paper models the behavioral rule set and improves and supplements the classical rules. Secondly, three modes for search task and target attracting task are constructed, and the mapping relationship between behavior rules and task modes is established. The switching mechanism of different task modes is given. Finally, the UAV swarm mission scenario is designed. The adaptive decision-making model proposed in this paper is compared with the decision-making method based on rule weighting in the MAE simulation environment. The simulation results prove that the boundary handling method is effective for improving the coverage. In the test of target attracting task effectiveness, the decision-making method proposed in this paper has more reasonable allocation results. The simulation results show a higher full-target monitoring rate, which proves the effectiveness and adaptability of the algorithm.

In the future work, we will establish more complex behavior modes and explore the mapping relationship between behavior modes and behavior rules to improve the effectiveness of UAV swarms.

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