

Article

Application Strategy of Unmanned Aerial Vehicle Swarms in Forest Fire Detection Based on the Fusion of Particle Swarm Optimization and Artificial Bee Colony Algorithm

Xiaohong Yan ^{1,2} and Renwen Chen ^{1,*} 

¹ College of Aerospace Engineering, Nanjing University of Aeronautics and Astronautics, Nanjing 210016, China; xiaohong_yan@nuaa.edu.cn

² College of Artificial Intelligence, Xinjiang Vocational and Technical College of Communication, Urumqi 831401, China

* Correspondence: rwchen@nuaa.edu.cn

Abstract: Unmanned aerial vehicle (UAV) swarm intelligence technology has shown unique advantages in agricultural and forestry disaster detection, early warning, and prevention with its efficient and precise cooperative operation capability. In this paper, a systematic application strategy of UAV swarms in forest fire detection is proposed, including fire point detection, fire assessment, and control measures, based on the fusion of particle swarm optimization (PSO) and the artificial bee colony (ABC) algorithm. The UAV swarm application strategy provides optimized paths to quickly locate multiple mountain forest fire points in 3D forest modeling environments and control measures based on the analysis of the fire situation. This work lays a research foundation for studying the precise application of UAV swarm technology in real-world forest fire detection and prevention.

Keywords: UAV swarm; forest fire detection; PSO and ABC algorithm



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1. Introduction

UAV swarm intelligence technology is a technology based on biological swarm behavior that realizes autonomous decision-making and intelligent division of labor among UAVs through perception interaction, information transfer, and cooperative work among UAVs and jointly accomplishes a specific task cost-effectively in a complex environment [1–3]. Depending on efficient data collection, analysis, and collaborative processing capabilities, UAV swarm technology has diverse applications in agriculture and forestry, including but not limited to crop monitoring, disease prevention, forest fire response, and precision plant protection [4–7].

With the advantages of cooperative operation, flexible adaptation, wide coverage, and cost-effectiveness, UAV swarm technology has a broad application prospect in the forest fire detection scenario. Liu (2023) proposed a hybrid algorithm based on the fireworks algorithm and a genetic algorithm for UAV forest fire reconnaissance task assignment [8]. Namburu (2023) studied forest fire identification in UAV imagery using x-mobilenet [9]. Liu (2023) researched a forest fire monitoring method based on UAV visual and infrared image fusion [10]. Wei (2023) proposed a hybrid algorithm for UAV path planning for rescue in bushfire environments [11]. However, previous approaches had less research on a systemic forest fire detection strategy based on UAV swarms, including fire point location, fire situation identification, and fire control.

In forest fire detection applications, UAV swarms carrying cameras and other sensors, utilizing self-organizing network communication technology, biome-like formation technology, and image recognition technology, should quickly reach forest fire starting points, accurately identify fire development, and make control measures. In complex forest environments, it is particularly important to rationally plan the course of action of

UAV swarms so that they can quickly and accurately reach the fire point. The particle swarm optimization (PSO) algorithm and the artificial bee colony (ABC) algorithm are two commonly used UAV path planning algorithms [12–16]. The PSO algorithm is a population intelligence optimization algorithm that simulates the feeding behavior of a flock of birds, features a fast speed of convergence, and is easily trapped in local optimal solutions. For example, Li (2024) researched a dynamic target search for multiple UAVs based on cooperative coevolution motion-encoded particle swarm optimization [17]. Ren (2021) proposed a cooperative search algorithm based on improved particle swarm optimization decisions for UAV swarms [18]. The ABC algorithm is a meta-heuristic optimization algorithm that solves complex optimization problems by mimicking the honey-harvesting behavior of a colony of bees. For instance, Lin (2022) studied an improved artificial bee colony algorithm based on multi-strategy synthesis for UAV path planning [19]. Liu (2021) researched a multi-UAV optimal mission assignment and path planning method for disaster rescue using an adaptive genetic algorithm and an improved artificial bee colony method [20]. Aslan (2019) implemented the artificial bee colony algorithm to solve UAV localization problems [21]. Li (2019) proposed a post-disaster UAV base station deployment method based on an artificial bee colony algorithm [22].

However, to achieve wide-area forest fire detection, UAV swarms require more than rational path planning. Forest fires often occur in high-temperature and arid wilderness forest areas, where fires spread rapidly and transportation and communication conditions are limited. UAV swarms need to prioritize the establishment of a good communication network to achieve formation flying and then accurately reach the fire point based on path planning algorithms [23–25]. Additionally, there is usually more than one fire point, so UAV swarms need to achieve large-scale, continuous, multi-target flight planning [26]. After arriving at a fire point, the UAV swarms need to judge the severity of the fire point, take preventive and control measures, and then detect the next fire point. Currently, there is a lack of research on systematic forest fire detection strategies based on fire point detection, fire assessment, and prevention measures based on UAV swarms.

The main contributions of this paper are presented as follows:

- An application strategy for UAV swarms in forest fire detection is put forward. In contrast to other detection methods, this study establishes a systematic forest fire detection strategy, including fire point detection, fire assessment, and control measures. The fusion detection method is conducted in the modeling of forest fire environments to verify the feasibility of the strategy. This strategy lays the foundation for research on large-scale forest fire detection and prevention based on UAV swarms in the real world.
- A fusion detection method based on the PSO and ABC algorithms is proposed. The fast convergence property of the PSO algorithm enables the UAV swarm to reach the fire point quickly. Upon reaching the fire point, the fusion detection method utilizes the ABC algorithm to make a judgment on the severity of the fire and make control measures, then continuously detects multiple fire points. The fusion detection method provides a new idea for the research of efficient and systematic forest fire detection methods.
- A forest fire 3D modeling environment has been established. Forest fires are characterized by a large fire range and multiple fire points, so the simulation of the fire environment needs to realize the fire scenarios with different heights of mountain peaks, different fire locations, and different fire ranges. The forest fire 3D modeling environment provides a good research condition for implementing the application strategy of UAV swarms in forest fire detection.

The rest of this paper is organized as follows: Section 2 formulates the problem of UAV swarm applied in forest fire detection. Section 3 introduces the methods of modeling forest fire 3D environment, detecting fire points, judging fire conditions, and making fire control measures. Section 4 offers the analysis and results through modeling and simulation to verify the feasibility of the application strategy of UAV swarm in forest fire detection. Finally, Section 5 presents the conclusion and outlines avenues for the next research.

2. Problem Formulation and Strategy Framework

In order to propose an effective forest fire prevention and control strategy, it is necessary to analyze the characteristics of forest fires and the operating environment of UAV swarms. Forest fires are characterized by large fire areas, rapid fire development, and multiple scattered fire points. Therefore, UAV swarms need to face a large-scale, complex, three-dimensional operating environment with multiple continuous fire targets with different heights and areas. Based on the above feature analysis, the application of UAV swarms in forest fire detection mainly faces three problems, as follows:

1. How do we reach the point of the forest fire in an efficient way? The challenge is to plan a reasonable path for the UAV swarm to navigate a complex, three-dimensional environment and reach the fire quickly.
2. How can we accurately assess the extent of the fire and make countermeasures? The difficulty of this problem lies in the identification of fire conditions, the establishment of a fire intensity assessment function, and how many UAVs are needed to prevent and control fires.
3. How do we establish a systematic forest fire detection strategy? A systematic forest fire detection strategy must achieve accurate detection and control of large-scale and multi-target mountain forest fires based on the methods of fire point detection, fire condition assessment, and fire control measures.

Figure 1 shows the scenario of UAV swarms applied to mountain forest fire detection. In order to solve the above problems in UAV swarms applied to forest fire detection, the framework of a systematic strategy is depicted in Figure 2, including modeling the forest fire 3D environment, planning the UAV swarm path, establishing the fire intensity assessment function, and making fire control measures.

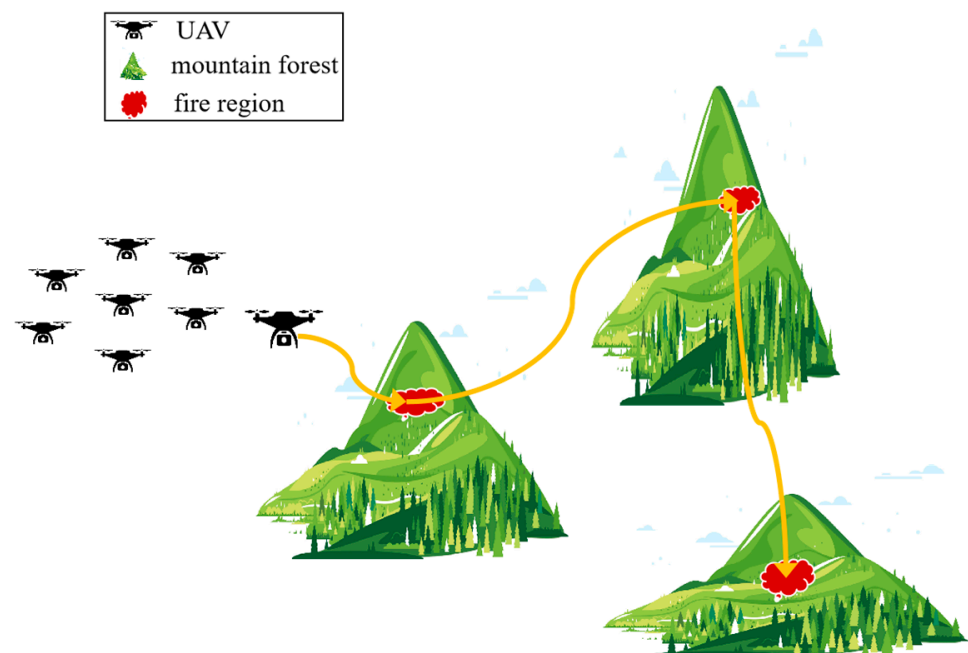


Figure 1. Scenario of UAV swarms applied to forest fire detection.

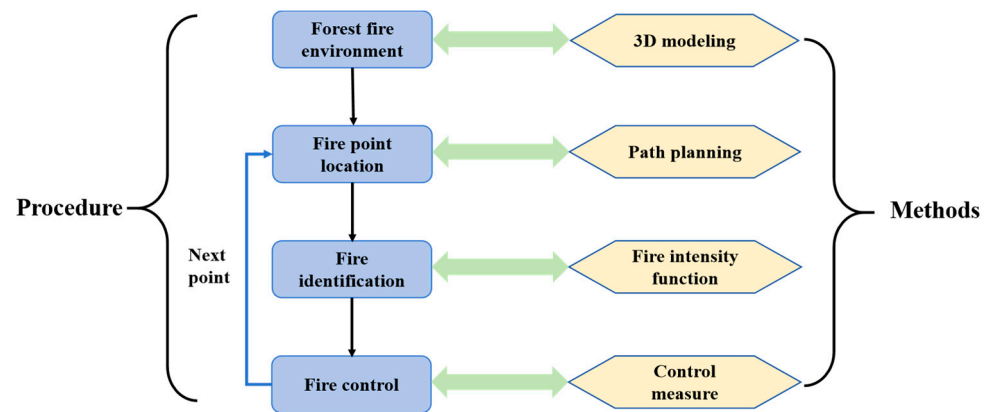


Figure 2. Framework for a systematic strategy of forest fire detection.

3. Methods

3.1. Three-Dimensional Environment Modeling

Efficient environmental modeling can enhance the path planning efficiency of UAV swarms, enabling them to swiftly reach the fire scene. In order to simulate the forest fire environment more realistically, different heights and widths of mountain forests, different positions, and different extents of fire points need to be successfully modeled. This paper takes into account the natural features of the terrain, particularly areas with obstacles, and various other factors relevant to environmental modeling. The exponential function is utilized to depict the mountain forest, and the mathematical representation of this model can be stated as follows [27,28]:

$$Z(x, y) = z_0 + \sum_{i=1}^n h_i \exp \left[- \left(\frac{x - x_i}{x_{si}} \right)^2 - \left(\frac{y - y_i}{y_{si}} \right)^2 \right] \quad (1)$$

where z_0 is the base terrain height, n is the number of mountain forests, x and y are the coordinates of the points projected by the model on the horizontal plane, z is the elevation value corresponding to the points on the horizontal plane, (x_i, y_i) is the center coordinates of the i_{th} mountain forest, h_i is the terrain parameter to control the altitude, and x_{si} and y_{si} are the attenuation to control the slope of the i_{th} mountain forest along the x -axis and y -axis, respectively.

When z_0 is set as 0, n is set as 1, (x_i, y_i) is set as (40, 40), h_i is set as 40, (x_{si}, y_{si}) is set as (8, 8), and the values of x and y are set from 0 to 100; the mountain forest is modeled in Figure 3. The fire point in the modeled mountain forest can be randomly generated. In Figure 3, with the height Z changes, the color of the mountain gradually changes from blue to yellow.

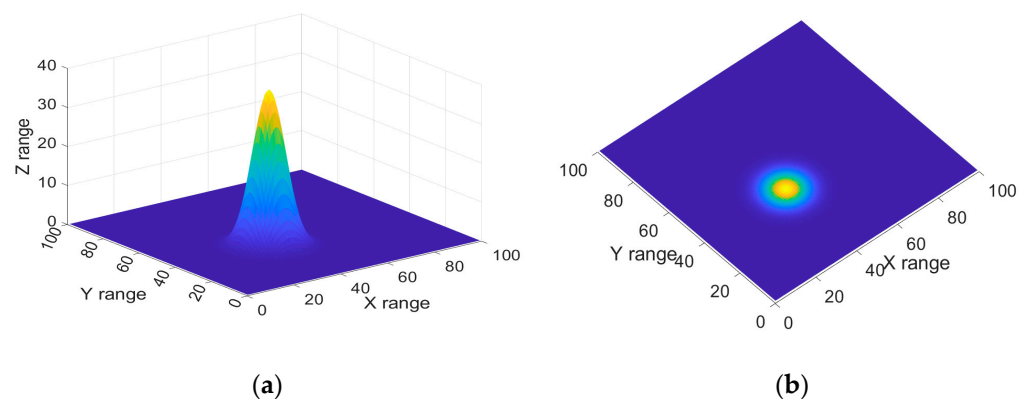


Figure 3. (a) Front view of the modeled mountain forest; (b) top view of the modeled mountain forest.

3.2. Fire Point Location

In the forest fire detection application, UAV swarms usually use a clustering network to transmit information [29–31]. The cluster head UAV needs to achieve rapid maneuvers, locate the fire point, and transmit the fire location to other UAVs. Therefore, in complex mountain forest environments, excellent UAV path planning algorithms are necessary to achieve rapid positioning of forest fires. The particle swarm optimization algorithm has been widely used in UAV path planning due to its fast convergence speed and easy implementation.

The particle swarm optimization algorithm utilizes points in the search space to simulate individuals in natural bird flocks. The foraging behavior process is likened to the iterative process of optimizing feasible solution transformations. The search process primarily relies on the fitness function for evolution without external information. Each individual approaches the optimal solution based on its individual extreme value and global extreme value. The particle swarm optimization algorithm supposes there is a particle population with a size M and an N -dimensional space search area, denoted as $X = [x_1, \dots, x_i, \dots, x_M]^T$. The i_{th} particle location can be described as $x_i = [x_{i1}, \dots, x_{i2}, \dots, x_{iN}]^T$, and its speed, that is, the distance the particle moving in each iteration can be expressed as $v_i = [v_{i1}, \dots, v_{i2}, \dots, v_{iN}]^T$. When the i_{th} particle passes through the position with the best fitness, the individual extreme value can be denoted as $P_i = [p_{i1}, \dots, p_{i2}, \dots, p_{iN}]^T$. When the entire population searches for the position with the best fitness, the global extreme value can be expressed as $P_g = [p_{g1}, \dots, p_{g2}, \dots, p_{gN}]^T$. The feasible solution to the optimization problem is the position of the optimized particle. Each iteration of the particle updates its position and velocity according to the following equations:

$$v_{id}^{k+1} = wv_{id}^k + c_1r_1(p_{id}^k - x_{id}^k) + c_2r_2(p_{gd}^k - x_{id}^k) \quad (2)$$

$$x_{id}^{k+1} = x_{id}^k + v_{id}^{k+1} \quad (3)$$

where v_i^k is the speed of the i_{th} particle in the k_{th} iteration, v_{id}^k is the d_{th} dimension component of v_i^k , x_i^k is the position of the i_{th} particle in the k_{th} iteration, x_{id}^k is the d_{th} dimension component of x_i^k , p_i^k is the individual extreme value of the i_{th} particle in the k_{th} iteration, p_{id}^k is the d_{th} dimension component of p_i^k , p_g^k is the global extreme value of the particle swarm in the k_{th} iteration, p_{gd}^k is the d_{th} dimension component of p_g^k , w is inertia weight, c_1 is the individual learning factor, c_2 is the group learning factor, r_1 and r_2 are random numbers uniformly distributed between $[0, 1]$, $1 \leq i \leq M$, $1 \leq d \leq N$.

In the UAV swarm applied to forest fire detection, the PSO algorithm is employed to find the particle locations of the optimal flight path of the UAVs. The fitness function of PSO is used to calculate the distance from the starting point position to the particle position and then to the ending point position, which determines the direction of the updated iteration of the particle positions. The best fitness is defined as the shortest flight path of the UAVs and can be expressed as follows:

$$Fitness = \min \left(\sum_{i=1}^{N1} \sqrt{(x_{i+1} - x_i)^2 + (y_{i+1} - y_i)^2 + (z_{i+1} - z_i)^2} \right) \quad (4)$$

where $(x_{i+1}, y_{i+1}, z_{i+1})$ and (x_i, y_i, z_i) represent the 3D coordinates at i_{th} and $i + 1_{th}$ path points in the UAV flight environment, respectively. $N1$ is the number of the path points, including the starting point, the particle position, and the ending point.

In addition to continuously optimizing the flight direction of the UAVs based on the fitness function, the PSO algorithm needs to be constrained by the terrain and environment. To avoid collisions, UAVs should always fly higher than the terrain height. Moreover, to

plan better paths and reduce costs, UAVs are stipulated to only work within designated areas. The constraints are expressed as follows:

$$1 \leq x_i \leq x_{max} \quad (5)$$

$$1 \leq y_i \leq y_{max} \quad (6)$$

$$Z(x_i, y_i) < z_i \leq z_{max} \quad (7)$$

where $(x_{max}, y_{max}, z_{max})$ represents the maximum range that UAVs can fly, $Z(x_i, y_i)$ represents the height of the mountain forest under the (x_i, y_i) coordinate according to the Equation (1).

In order to ensure the feasibility of the UAV flight trajectory and reduce the algorithm calculation time, it is necessary to smooth the flight trajectory. Since the flight path of the UAV is related to ordered spatial point coordinates, this paper utilizes a cubic B-spline interpolation algorithm to smooth the flight path [32–34]. The sequence of coordinates of the space points flown by the UAV can be represented as $\{S, T_1, T_2, \dots, T_{N1}, E\}$, where S is the starting point coordinate, E is the ending point coordinate, T_i is the particle point coordinate from the particle swarm optimization algorithm. Based on the cubic B-spline interpolation algorithm, the (X_t, Y_t, Z_t) coordinates of any point in the smoothed UAV flight path can be represented as follows:

$$X_t = \sum_{i=0}^m X_i F_{i,k}(t) \quad (8)$$

$$Y_t = \sum_{i=0}^m Y_i F_{i,k}(t) \quad (9)$$

$$Z_t = \sum_{i=0}^m Z_i F_{i,k}(t) \quad (10)$$

where (X_i, Y_i, Z_i) represents the coordinate of the control point in the cubic B-spline interpolation algorithm, $F_{i,k}(t)$ represents cubic B-spline basis function, k is the order, m is the number of control points.

The procedure for mountain forest fire point location based on the UAV swarm path planning algorithm is illustrated in Figure 4. Firstly, initialize particle swarm parameters, such as the particle swarm size, dimension, number of iterations, inertia weight, learning factor, and so on. Secondly, randomly initialize the position and velocity of each particle, record the individual optimal position and the group optimal position, and calculate the fitness value of each particle according to Equations (4) and (8)–(10). Thirdly, check if the particle's position complies with the stipulated conditions according to Equations (5)–(7). Fourthly, update the velocity and position of each particle according to Equations (2) and (3). Fifthly, update the historical optimal fitness value and position of each particle and the group until the iteration is completed. Finally, output the particle position and draw the UAV flight path diagram along with the mountain forest fire location.

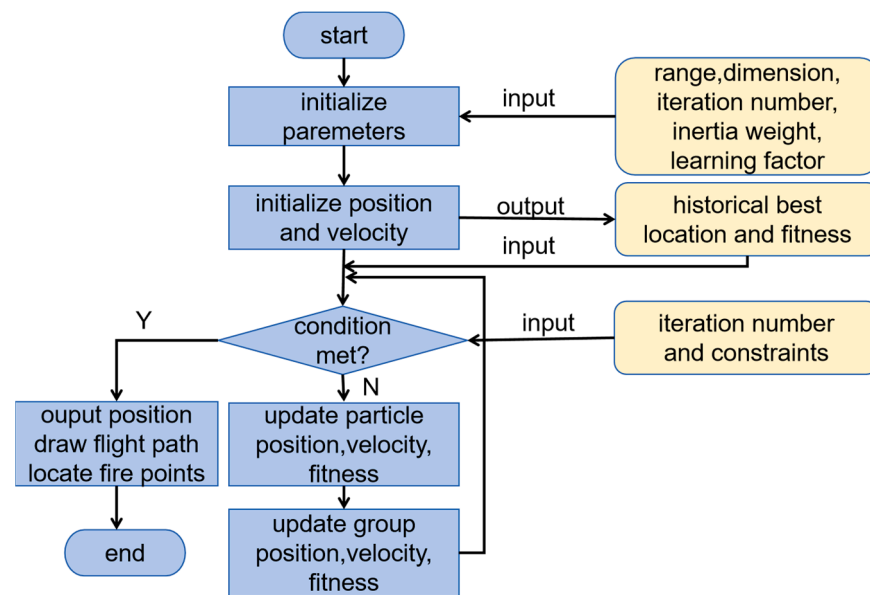


Figure 4. Procedure for fire point location.

3.3. Fire Point Identification and Control

The UAV path planning algorithm can be utilized to quickly locate a mountain forest fire point. However, to systematically detect forest fires, it is necessary to first locate the mountain forest fire point, then identify the fire severity and make control measures. Therefore, a mechanism for identifying and controlling mountain forest fire points is required.

The artificial bee colony algorithm is a global optimization algorithm based on swarm intelligence that was proposed by Turkish scholar Karaboga in 2005 [35]. The algorithm is inspired by the honey-harvesting behavior of bees in nature and finds the optimal solution to the problem by simulating the division of labor, cooperation, and information-sharing mechanisms of bees. In the ABC algorithm, bees are divided into three categories: hired bees, observation bees, and scout bees. The hired bees are responsible for searching for new honey sources in the solution space and updating their positions according to the quality of the honey sources. The observer bees choose between the honey sources found by the hired bees to decide whether to follow a certain honey source. When the scout bees encounter a food source, they will abandon current food sources and explore new food sources.

The specific implementation steps of the ABC algorithm are as follows: Firstly, initialize each nectar source and set the relevant parameters, including the number of nectar sources, iterations, and so on. Secondly, assign a hired bee to each nectar source, search to generate new nectar sources according to Equation (11), and calculate the fitness. Thirdly, observation bees choose the nectar source according to the greedy strategy and calculate the probability of choosing the nectar source according to Equation (12). Fourthly, when all the hired bees and observers have searched the entire search space, the scout bees search for new possible solutions using Equation (13). Lastly, loop the above operations until the termination condition is met and output the optimal solution.

$$v_{id} = x_{id} + \varphi(x_{id} - x_{jd}) \quad (11)$$

$$pr_i = fit_i / \sum_{i=1}^{NP} fit_i \quad (12)$$

$$v'_{id} = x_{id}^{min} + r * (x_{id}^{max} - x_{id}^{min}) \quad (13)$$

where v_{id} and v'_{id} represent the new nectar sources, pr_i represents the probability of choosing the nectar source, pr_i represents the probability that the observation bee follows the nectar

source, fit_i represents the fitness, NP represents the number of nectar sources, x_{id}^{max} and x_{id}^{min} represent the maximum and minimum values of nectar source locations, φ is a random number of $[-1, 1]$ on the interval, and r is a random number of $[0, 1]$ on the interval.

A mechanism for mountain forest fire point identification and control can be set up based on the ABC algorithm. When arriving at the fire point location, the cluster head UAV can be defined as the hired bee, and the other member UAVs can be defined as the observation bees. UAVs carry relevant sensors to detect the fire through image processing methods. The cluster head UAV (hired bee) quickly reaches the center of the fire, and the other member UAVs (observation bees) detect the overall fire situation. The severity of the fire corresponds to the fitness of the nectar source in the ABC algorithm. Based on the image recognition algorithms, the situation of the fire (the fitness of the nectar source) can be identified. A mountain forest fire control mechanism can be set up to assign how many UAVs to fight fires according to the fire situation. The fire control mechanism corresponds to the observation of bees following the nectar source according to the probability provided by Equation (12) in the ABC algorithm. When the mechanism of fire identification and control is set up, the cluster head UAV turns to the scout bee to detect the next fire point. The entire procedure for mountain forest fire point identification and control is illustrated in Figure 5.

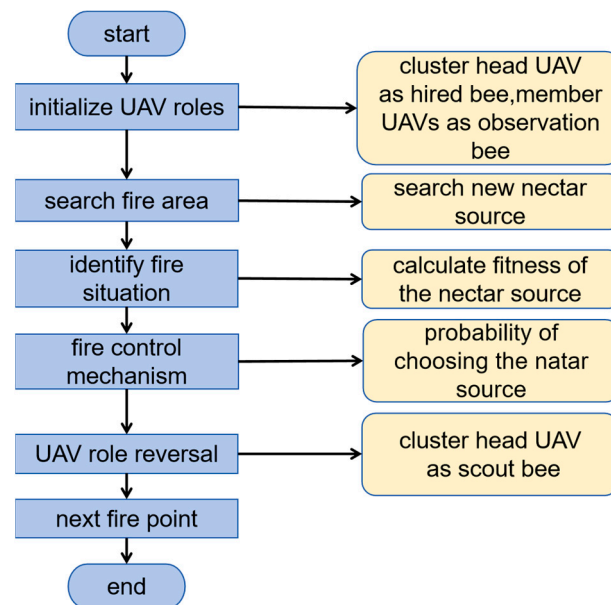


Figure 5. Procedure for fire point identification and control.

3.4. Strategy Establishment

In order to simulate a real mountain forest fire scenario, a 3D mathematical model of the mountain forest based on the exponential function is set up first. Next, the particle swarm optimization algorithm is used for the UAV path planning to quickly locate the fire points. It should be noted that the constraints of UAV flight need to be met, and the cubic B-spline interpolation algorithm is implemented to smooth the UAV flight path. Then, the artificial bee colony algorithm is implemented to set up a mechanism for mountain forest fire point identification and control. In the mechanism, UAVs play different roles, and the methods of fire identification and control are proposed. Finally, a strategy for mountain forest fire detection based on UAV swarms is established to achieve fire point location, identification, and control. The setup procedure for the application strategy is illustrated in Figure 6.

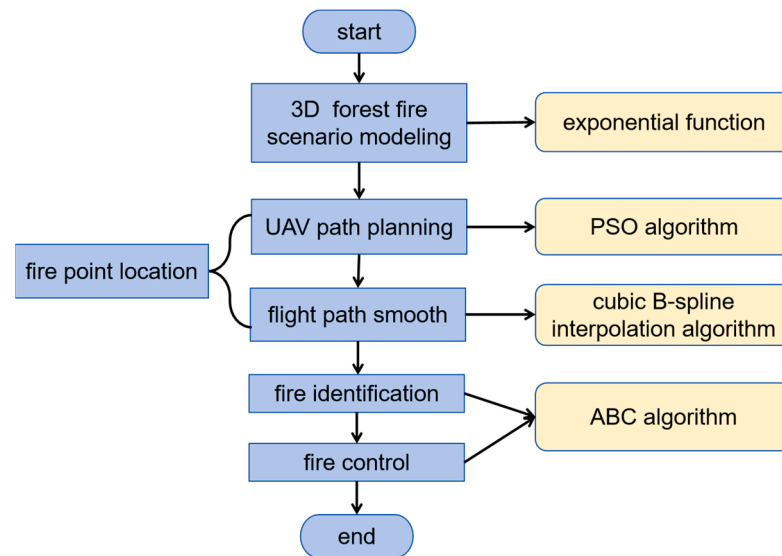


Figure 6. Procedure for the UAV swarm strategy for mountain forest fire detection.

In addition, to enhance the robustness of the system in response to unforeseen situations encountered during the flight of drone swarms, a multi-sensor redundancy strategy is employed. This strategy ensures that even if a single sensor fails, the drone swarm can still achieve cooperative flight and autonomous obstacle avoidance. Prior to drone flight, a detailed investigation and analysis of the terrain, weather, and communication conditions of the area to be surveyed are conducted, and emergency plans are prepared in advance to address unexpected circumstances.

4. Results

The strategy proposed in this paper is fully programmed, simulated, and verified in the MATLAB R2022b environment. The main configuration of the hardware environment is a Win11 desktop, 13th Gen Intel® Core™ i7-13700F, 2.10 GHz, and 16 GB RAM.

4.1. Scenarios Setup

According to the modeling method described in Section 3.1, the models of mountain forests are configured as illustrated in Figure 7. As can be seen from the top view, five mountain forests with different heights and widths are constructed, the UAV flight range (x, y, z) is set from $(0, 0, 0)$ to $(100, 100, 100)$, and the fire points with different locations are specified on the mountain forest models. It should be noted that the characteristics of the modeled mountain forests and fire points are all randomly selected. The specific parameters of the modeled mountain forests and fire points utilized in the UAV swarm application strategy verification are detailed in Table 1.

Table 1. Characteristics of the modeled mountain forests and fire points.

Parameters	M1	M2	M3	M4	M5
z_0	0	0	0	0	0
(x_i, y_i)	(25, 45)	(53, 27)	(62, 36)	(75, 75)	(52, 85)
h_i	67	71	37	75	80
(x_{si}, y_{si})	(7, 8)	(6, 5)	(7, 9)	(3, 3)	(9, 9)
fire location (x, y, z)	(44, 59, 30)	(42, 20, 35)	(87, 45, 42)	(25, 50, 48)	(74, 73, 44)

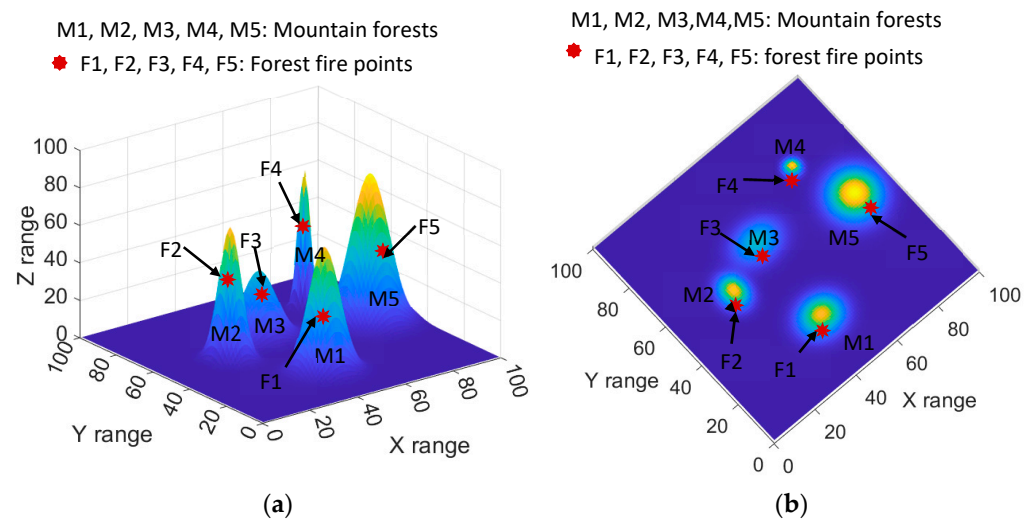


Figure 7. (a) Front view of the five modeled mountain forests and fire points; (b) Top view of the five modeled mountain forests and fire points.

4.2. Multiple Fire Points Location

To accurately locate the continuous multiple mountain forest fire points, the particle swarm optimization algorithm is implemented for UAV swarm path planning. Firstly, the parameters of the particle swarm are initialized, including the particle population M , the number of the iteration k , the inertia weight w , the individual learning factor c_1 , the group learning factor c_2 , the location boundary area, and the starting point of the UAV flight. It should be noted that those parameters are selected based on the standard PSO algorithm [36]. The specific parameters for initializing the particle swarm are detailed in Table 2.

Table 2. Parameters for initializing the particle swarm.

Parameter	Value
M	50
k	100
w	1.2
c_1, c_2	2, 2
location boundary area	(0, 0, 0) to (100, 100, 100)
starting point	(0, 0, 0)

Secondly, to ensure the feasibility of the UAV flight trajectory and reduce the algorithm calculation time, the cubic B-spline interpolation algorithm is implemented to smooth the flight trajectory. To guarantee the effective execution of the cubic B-spline interpolation algorithm, each particle is set to consist of three positions, which means that there are three location points in each UAV flight path to connect the starting and ending points. Furthermore, in order to avoid collisions, UAVs should always fly higher than the terrain height in the flight path, which means that the height of a UAV flight should exceed the height of a mountain forest, according to Equation (7). Additionally, the distance between the starting and ending points is defined as fitness. In order to obtain accurate fitness and fire point locations, the models of mountain forests should be interpolated and refined.

Based on the above settings and preparations, the results of the UAV flight path to locate the forest fire points are illustrated in Figures 8 and 9. As can be seen, with the height Z changes, the color of the mountain gradually changes from blue to yellow, the stars represent fire points and squares represent start point.

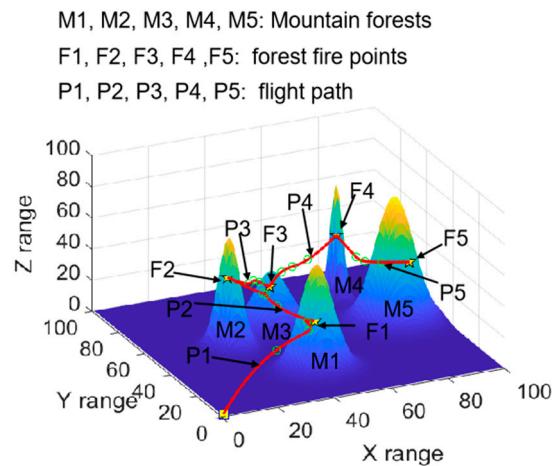


Figure 8. Front view of UAV flight path on locating fire points.

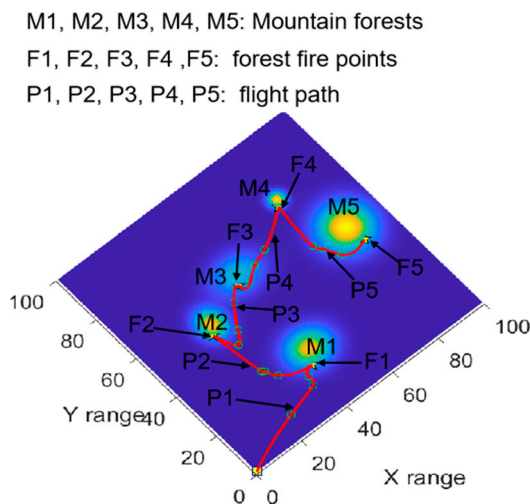


Figure 9. Top view of the UAV flight path for locating fire points.

As shown in Figure 8, the UAV departs from the starting point (0, 0, 0), initially reaches Fire Point F1 at a relatively high position of the mountain forest M1, then proceeds to Fire Point F2 of the mountain forest M2, next proceeds to the Fire Point F3 at a relatively low position of the mountain forest M3, after that proceeds to the Fire Point F4 of the mountain forest M4, ultimately arriving at the Fire Point F5 of the mountain forest M5. As can be seen, the UAV flight path planning method realizes the detection of multiple continuous mountain forest fire points at different heights and locations. It is important to highlight that each path is connected by three location points, and all the paths successfully avoid the adjacent mountain forests. In order to show more detailed features of the method for detecting continuous multiple mountain forest fire points, Figure 9 illustrates the top view of the UAV flight path.

As depicted in Figure 9, the UAV flight paths P1, P2, P3, P4, and P5 are shown more directly, highlighting the details of the flight trajectory successfully bypassing the adjacent mountain forests. It is important to note that all optimal fitness can be obtained after 62 iterations of the PSO algorithm. The computation times of the flight paths P1, P2, P3, P4, and P5 are 13.3 s, 7.9 s, 9.1 s, 11.2 s, and 13.1 s, respectively. Figure 10 illustrates how optimal fitness evolves with the number of iterations. As can be seen, flight Path2 has the fastest rate of optimal fitness decline, flight Path3 and Path4 have the middle rate, and flight Path1 and Path5 have a relatively slow rate, aligning with the progression of optimal path adjustments.

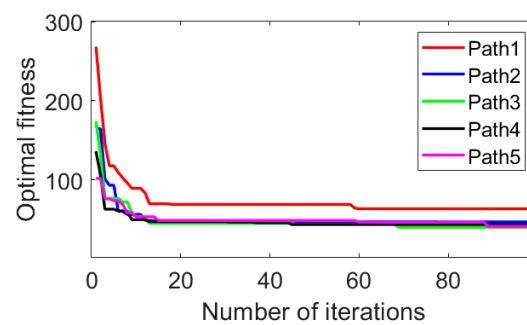


Figure 10. Process for optimal fitness change.

Based on the above result and analysis, the continuous multiple mountain forest fire points with different heights and locations are located by implementing the PSO algorithm. The UAV flight path is optimized using the cubic B-spline interpolation algorithm, ensuring a smooth trajectory that navigates around the adjacent mountain forests. The successful location of the fire points lays the foundation for subsequent fire identification and control.

4.3. Fire Identification and Control

After the fire points are located by the cluster head UAV (hired bee), the other member UAVs (observation bees) start to assess the specific fire situation in the ABC algorithm-based mechanism for identifying and controlling mountain forest fire points. In this mechanism, the member UAVs (observation bees) are employed to explore the area and severity of the fire point. Typically, the member UAVs (observation bees) are equipped with multi-function sensors, enabling accurate identification of fire severity through image recognition algorithms. To quantify the process of fire identification and control, a series of height projections on the horizontal plane of the simulated mountain forest is used to indicate the fire area, with the highest point representing the severity of the fire and the product of the fire area and severity representing the fire control function. The forest fire identification and control mechanism can be mathematically expressed as follows:

$$A_f = \sum_i^R Z(x_i, y_i) \quad (14)$$

$$S_f = \max(Z(x_i, y_i)) \quad (15)$$

$$F_{ctrl} = A_f \times S_f \quad (16)$$

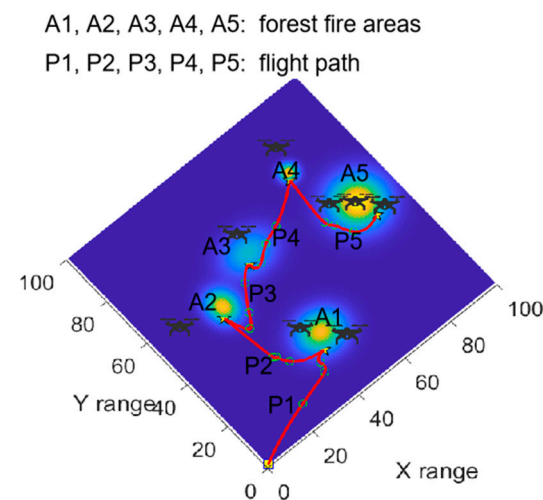
where A_f represents the fire area, S_f represents the fire severity, F_{ctrl} represents the fire control function, $Z(x_i, y_i)$ represents the height of the mountain forest under the (x_i, y_i) coordinate according to Equation (1), and R represents the max value of x_i and y_i .

According to the above-modeled mountain forests and fire points, the characteristics of the fire point situations are shown in Table 3. In order to demonstrate the mechanism of fire identification and control visually, the representational model is depicted in Figure 11. It is evident that Fire Point F5 has a larger area and more severe fire conditions, resulting in a higher F_{ctrl} value and requiring more UAVs to extinguish the fire. It should be noted that the quantity of UAVs at various fire points in Figure 10 only signifies an estimated amount and not a precise one.

Upon completion of the fire identification and control at the current fire point, the cluster head UAV (hired bee) transitions into a scout bee to locate the next fire point, marking the completion of the closed loop of the ABC algorithm. Building on the above results and analysis, the mechanism of identifying and controlling mountain forest fire points based on the ABC algorithm is established, offering a new research foundation for the precise management of mountain forest fires in the real world.

Table 3. Characteristics of the fire point situations.

Parameters	A_f	S_f	F_{ctrl}
Fire Point F1	11787	67	789729
Fire Point F2	6692	71	475132
Fire Point F3	7323	37	270951
Fire Point F4	2121	75	159075
Fire Point F5	20207	80	1616560

**Figure 11.** Modeling of fire identification and control mechanisms.

5. Discussion

The above results demonstrate the feasibility of the systematic application strategy of UAV swarms in forest fire detection, including fire point detection, fire assessment, and control measures. The particle swarm optimization (PSO) algorithm is employed to provide optimized paths to quickly locate multiple mountain forest fire points in 3D forest modeling environments, and the artificial bee colony (ABC) algorithm is employed to analyze the fire situation and provide control measures. The continuous multiple mountain forest fire points with different heights and locations can be located, assessed, and controlled by implementing the systematic application strategy of UAV swarms.

However, there are some drawbacks to this paper. In UAV path planning, the standard PSO algorithm has the shortcomings of being easy to fall into the local optimal solution, unstable search speed, and sensitive parameter selection. In the fire identification and control mechanism, the standard ABC algorithm does not give a specific quantification method for identifying and controlling the fire.

Moreover, there are relatively few constraint parameter settings in this simulation model. In the real world, more factors will affect the UAV swarm's flight path and fire identification. Fortunately, the existing deficiencies can be continuously optimized and improved, building upon the application strategy proposed in this paper and paving the way for further in-depth research in the future.

6. Conclusions

This paper explores an application strategy for UAV swarms in mountain forest fire detection. We propose an application strategy for UAV swarms for mountain forest fire detection based on a fusion of the PSO and ABC algorithms. Specifically, we establish a 3D mountain forest fire scenario, implement the particle swarm optimization algorithm for the UAV path planning to swiftly locate the fire points, and employ the artificial bee colony algorithm for the mountain forest fire point identification and control. The findings of this

work could serve as valuable references for studying UAV swarm technology in real-world mountain forest fire detection.

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