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Minimum Time Search Path Planning for Multiple Fixed-Wing Unmanned Aerial Vehicles with Adaptive Formation

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ABSTRACT: Planning the flight path for a fleet of fixed-wing unmanned aerial vehicles during search and rescue operations poses a significant challenge as it requires minimizing search time and optimizing the formation of the unmanned aerial vehicles. This paper proposes a novel integration of a leader-follower formation flight technique for multiple fixed-wing unmanned aerial vehicles with a minimum-time search path planning algorithm. In the first step, the proposed algorithm, based on continuous ant colony optimization, plans a sequence of safe and feasible waypoints for the leader while determining appropriate azimuth angles for the followers. In the next step, the algorithm utilizes a nonlinear three-degree-of-freedom model, developed based on a leader-follower formation flight technique, to plan the followers' flight paths. Applying Dubins curves based on kinematic constraints of the unmanned aerial vehicles not only reduces computational time but also ensures the feasibility of the best search paths between planned waypoints. Furthermore, in the presence of static obstacles, a developed function in the planning process addresses collision and obstacle avoidance constraints. The effectiveness and performance of the suggested method in detecting targets in minimum-time search missions and the ability of the planner to reconfigure the formation of unmanned aerial vehicles in cluttered environments are demonstrated through comprehensive simulation studies and Monte Carlo analysis.

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1- Introduction

The rapid growth in the use of unmanned aerial vehicles (UAVs) in recent years can be attributed to their cost-effectiveness, compact size, high speed, and agility, leading to an expanded range of applications, including scenarios with inherent risks. These versatile aircraft serve multiple purposes, such as locating survivors in the aftermath of natural disasters, conducting maritime search and rescue (SAR) missions, and aiding in the search for missing persons in remote forest or wilderness areas [1, 2]. Drawing inspiration from traditional human search and rescue operations, UAVs enable rescue teams to effectively patrol and access hard-to-reach locations during SAR missions [3, 4].

Compared to using a single unmanned aerial vehicle (UAV), employing multiple UAVs that work together collaboratively can lead to more effective and efficient operations due to their redundancy and ability to cooperate during mission execution. These sensors (UAVs) have the potential to enhance sensing flexibility, reduce search times in a wide area, and therefore effectively speed up and improve SAR operations. Furthermore, various emergency scenarios necessitate the use of multiple UAVs .[5]. Utilizing multiple UAVs in predefined formations during search missions has the advantage of covering and sweeping a wide area in minimal time. Research on formation flight typically focuses on methods to maintain the desired formation through tracking control [6] or regulation control [7] techniques.

Formation path planning algorithms can be categorized into traditional and intelligent approaches. The traditional algorithms are such as the Dijkstra algorithm [8], and the Voronoi diagram [9], and the new ones are categorized as evolutionary-based planning methods and machine learning-based methods. The most popular evolutionary-based algorithms for formation flight in literature are the genetic algorithm (GA) [10], particle swarm optimization (PSO) [11], and ant colony optimization (ACO) [12]. Machine learning-based strategies include neural network (NN) [13], reinforcement learning (RL) [14], and deep reinforcement learning (DRL) algorithms [15] that simulate human learning behavior for multi-UAV formation control. Usually, in most formation flight missions, the UAVs avoid changing the formation, but in a different strategy because of some limitations or constraints, such as malfunctions, collision avoidance, member replacement, and fuel savings, the formation of the UAVs must be changed. The formation reconfiguration is an optimal control problem in the presence of some constraints, and there are a variety of solutions in the literature for it [16]. Harikumar et al. [17] proposed an Oxyrrhis Marina-inspired search and dynamic formation control (OMS-DFC) framework for multi-UAV systems to

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search forest fires in an unknown environment. Chen et al. in [18] proposed a trajectory planning method based on Dubins trajectory and the PSO algorithm in a mission with formation reconstruction. To conduct an exhaustive search of mobile ground targets, Brown et al. proposed a dynamic spiral-out formation for a team of UAVs [19].

Optimizing cooperative search missions involves considering various objective functions. These functions are divided into two general categories: entropy-related and detection-related functions. While entropy-based measures face challenges in detecting non-Gaussian targets, detection-related functions offer a wider range of applications [20]. In a one-sided search problem where the object's motion model is independent of the searcher's actions [21], different objective functions can be considered based on the mission's goal. Some of these objectives can be listed as maximizing the probability of target detection [22], maximizing the information gain [23], maximizing the surveillance coverage [24, 25], maximizing the time-discounted reward [26], minimizing the search time for finding all targets, or maximizing the number of target detections [27]. Finding one or several targets immediately in unknown locations is essential in MTS problems to meet the minimum time requirements. Additionally, the MTS effectively utilizes information on the target's location and dynamics from sources like maps and witnesses to increase the likelihood of detection [28]. Optimization approaches based on probabilistic theory and bioinspired algorithms are often used to solve MTS problems [29]. As a result of uncertainty in the sensors' performance and the location and dynamics of the targets, we cannot estimate an exact target detection time for a search trajectory. References such as [28, 30] minimize the expectation of the detection time (ET) by modeling the uncertainty sources with a probability function model. The effectiveness of the MTS strategy based on the ET as a detection-related function has been successfully approved in recent works [28-32], for aircraft with different constraints.

The authors' findings show that previous references separately consider the problem of minimum time search and reconfiguration of the formation flight of a fleet of UAVs. In addition, they don't discuss minimum time search in the configuration of adaptive formation flight of fixed-wing UAVs. This study proposes a minimum-time search algorithm for a team of fixed-wing UAVs that fly in an adaptive formation to find a static survivor in a limited environment with strict static obstacles. Where the environment is certain and prior knowledge is available for the UAVs. In this regard, the main contributions of this paper are summarized as follows:

- This study integrates the minimum time search approach with adaptive formation flight using a leader-follower strategy to maximize instant coverage by multiple UAVs while preventing overlapping search trajectories.
- The continuous ant colony optimization algorithm (ACO_R) [33] is utilized to simultaneously plan optimal waypoints for a leader and optimal azimuth angle for followers in the configuration of formation flight of UAVs.
- To address challenges related to kinematic constraints and computational complexity in path planning, the analytical Dubins method [34] is integrated with the minimum-time search algorithm.
- The proposed algorithm simultaneously considers various constraints, including obstacle and collision avoidance, kinematic constraints, and communication constraints, when planning minimum time search paths for all members of the team.

The remainder of this paper is organized as follows: Section 2 outlines the modeling of the search problem and the utilization of formation flight for multiple fixed-wing UAVs in this context. Sections 3 and 4 introduce the continuous ant colony algorithm as an optimization algorithm to find MTS paths and address various constraints associated with this problem. Section 5 illustrates the MTS algorithm in the framework of the formation flight of multiple UAVs to achieve maximum coverage in each instance of the search mission. Section 6 simulates different search scenarios and performs statistical analysis to illustrate the performance of the proposed algorithm. Finally, Section 7 presents a discussion and conclusion based on the obtained results.

2- Modeling the problem

This section describes the mission environment, target, sensor, and UAV models for the initialization of the search problem. It is assumed that all UAVs have initial information about the environment and obstacles, and their knowledge of the environment updates based on the information they detect with their detection sensors and the data they share with each other. Also, it is considered that each UAV independently estimates the position of the target in a decentralized fashion.

2- 1- Mission environment and target probability map

In this work, it is assumed that the search environment can be simplified to a two-dimensional space by considering that all UAVs maintain a constant altitude while flying in formation. The target probability map illustrates the distribution of targets within the defined search area and provides information on potential target locations throughout the search mission. This probability map is represented on a grid map with dimensions $N_x \times N_y$, where each grid cell contains the probability of the target's presence. If each cell of the grid in time t has a target existence probability defined by v^t, the target probability map (belief map) can be derived with $b(v^t) = P(v^t)$. Here, the $P(v^t)$ is a probability distribution function (PDF) to model the probable target's location at time t based on the available information. In an initial probability distribution ($t = 0$), the probability of targets appearing on all grid cells of the map equals one as follows [30]:

$$\sum_{v^0 \in N_x \times N_y} b(v^0) = 1 \tag{1}$$

If the target detection sensor of the UAVs is configured to focus on a single cell in its field of view, the probability map can be continually updated through recursive Bayesian estimation. The estimation procedure for stationary targets can be succinctly described by Eq. (2) [30]. This method updates the belief of the unobserved probability over the map using the information provided by the sensors of the UAVs as they traverse each cell of the grid. Through this iterative process, the algorithm can make more precise decisions about where to look for targets.

$$b(v^t) = \prod_{u=1:U} P(z_u^t \mid v^t, r_u^t) \sum_{v^{t-1}} b(v^{t-1}) \tag{2}$$

Where, z_u^t, r_u^t, and v^t are sensor measurements, the location of the uth UAV, and the target position at time t, respectively. Also, P is the probability model of the target detection sensor.

2- 2- UAV model

In this paper, we consider three homogeneous fixed-wing UAVs with the same performance constraints that fly at a constant altitude (means $\gamma = 0$) in their entire flight paths. Various linear and non-linear mathematical models can be employed to represent the flight behavior of fixed-wing UAVs [35, 36]. In many cases, kinematic models are sufficient for path-planning tasks because they can accurately predict the motion of the UAV without considering the detailed dynamics of the system. This simplification decreases computation time and enhances the efficiency of planning algorithms. In two-dimensional space, under the assumption that the mass of the flying vehicle does not change and considering heading rate as the UAV's control input, by using first-order dynamics, the kinematic model for each UAV about the vertical axis of its body-frame reference can be written as follows [37]:

$$\begin{aligned} &\dot{x} = V \cos \chi \\ &\dot{y} = V \sin \chi \\ &\dot{\chi} = command \quad , \left| command \right| < (\dot{\chi}_{\max} = V / R_{\min}) \end{aligned} \tag{3}$$

Where (x, y) displays the UAV's horizontal position, V is airspeed, $R_{\min}$, and χ are the minimum level turn radius and heading angle of the UAV, respectively.

2- 3- Target Model

Various methods can be used to model targets in search and rescue missions. The most popular models used for modeling different targets include the generic target model, the Markovian target model, the random target model, the deterministic model, and the model of decaying certainty [26]. As a useful and applicable method, the probability map can be used to model the presence of the target in a wide search area [38, 39]. This study focuses on a scenario where a stationary target is located in a known environment, but its precise position is uncertain. Information is available about specific regions with a high probability of target presence within the context of a target probability map. The target, assumed to be a survivor, is considered to be capable of emitting radio signals symmetrically or being visually detectable from all directions. The probability of the survivor's presence in each cell of the network remains constant over time. Additionally, it is assumed that if the survivor is within the range of the UAV's sensor, it will be accurately identified.

2- 4- Sensor model

Some assumptions are usually used for the sensor model to simplify the search and make updating the probability map convenient [40, 41]. It is assumed that all UAVs are equipped with identical downward-looking sensors for the detection of survivors, and the sensor position coincides with the position of the UAV. The detection sensor of all UAVs has a disk-shaped footprint with a radius R_s. This radius is influenced by the UAV's altitude, but we considered a constant altitude to return the best detection capability or resolution for UAVs. Generally, two potential target sensor measurements are taken into account, depending on whether the target is present inside the sensor detection disk or not. By defining z_u^t, r_u^t, and v^t, the probability model of the sensor can be expressed as:

$$\begin{cases} P(z_u^t \mid v^t, r_u^t) = 1 & if \;\; d(r_u^t, v^t) \le R_s \;\; and \;\; z_u^t = D \\ P(z_u^t \mid v^t, r_u^t) = 0 & if \;\; d(r_u^t, v^t) > R_s \;\; and \;\; z_u^t = \overline{D} \end{cases} \tag{4}$$

In which $d(r_u^t, v^t)$ illustrates the horizontal Euclidean distance between the target and the UAV and $P(z_u^t \mid v^t, r_u^t) = 1$ means the uth UAV and target are simultaneously at a distance smaller than R_s. The $z_u^t = D$ and $z_u^t = \overline{D}$ show detection and non-detection of the target by the UAV, respectively. It is assumed that the search process will stop after the first detection.

2- 5- The structure of the formation

Among the various formation strategies, such as behavior-based, leader-follower formation, and the virtual structure approach [42], we used the behavior-based method proposed in [43] to ensure that the followers follow the leader in an appropriate azimuth angle. To achieve the desired formation, this approach generates appropriate acceleration commands to adjust the position and velocity of the followers relative to the leader. Our research focused on a formation flight involving three fixed-wing UAVs, comprising a leader and two followers. It is assumed that all UAVs have the same performance constraints and are equipped with the same sensors for target detection (featuring a detection disk with a specific radius R_s). By assuming that UAVs only fly in the horizontal plane, Fig. 1 shows the typical navigation model of the followers in the local ($X_l Y_l$) and inertial ($X_I Y_I$) frames. Fig. 1 displays three UAVs in the configuration of a leader-follower formation, where two followers are symmetrically

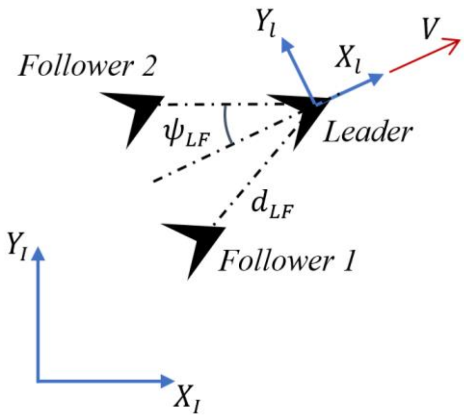


Fig. 1. Illustration of the azimuth angle between the followers and leader in the local frame

placed at a distance of d_{LF} and an azimuth angle of ψ_{LF} relative to the leader. The behavior-based formation strategy tries to maintain the relative distance and azimuth angle between the leader and followers throughout the entire flight path. To achieve this goal, the speed and direction of movement of the followers must be adjusted according to the velocity vector (V) of the leader. By aligning a local frame's *X*-axis with the leader's velocity vector (as shown in Fig. 1), the followers' positions in the local frame are determined using Eq. (5).

$$\begin{cases} X_{l_{F1}} = -d_{LF}\cos\psi_{LF} \\ Y_{l_{F1}} = d_{LF}\sin\psi_{LF} \end{cases} \quad \begin{cases} X_{l_{F2}} = -d_{LF}\cos\psi_{LF} \\ Y_{l_{F2}} = -d_{LF}\sin\psi_{LF} \end{cases} \tag{5}$$

It is assumed that the distance between each follower and leader is fixed and equal $2R_s$, to ensure collision avoidance between them. To prevent collisions between the followers, it is also important to maintain a minimum safe distance between them during the reconfiguration process. Since UAVs can cover a circular area with a radius of R_s, it is necessary to consider a minimum safe distance $2R_s$ to prevent overlap regions observed by followers. (The minor variations in the UAV's flight altitude are ignored). Based on the considered distances between the members of the team and the assumption of a symmetrical formation, the azimuth angle (a parameter that is optimized in the minimum time search process) can continuously vary from 90˚ to 30˚. Therefore, the position of followers relative to the leader in the local frame can range from Form (A) to Form (B) as depicted in Fig. 2. Forms (A) and (B) represent configurations for maximum and minimum coverage bandwidth during search operations, respectively. The region covered by all UAVs has a bandwidth ranging from $4R_s$ to $6R_s$, as illustrated in Fig. 2.

2- 6- Objective function for the search problem

The objective of the minimum time search approach is to minimize the time spent searching and detecting a specified lost target. Uncertainties such as the unspecified exact target location and dynamic make it impossible to determine the exact target detection time for planned search paths. To overcome the uncertainty related to the MTS problem, [28-32] recommends optimizing the expected value of the target detection time rather than the exact target detection time.

In this work, the expected value of target detection time for the trajectories, $ET(r_{1:U}^{0:t})$, is considered based on [30] as the main objective function criterion. Generally, a probability function model is used to formulate the MTS objective function. This function is calculated based on Eq. (6) by adding up the probability of not detecting the target $P(z_{1:U}^{1:t} = \bar{D} \mid r_{1:U}^{0:t})$ up to each time step for a specific horizon time *T*. The probability that the target remains undetected at the time t is determined by the cumulative sum of all cell values in the unnormalized probability map, $\tilde{b}(v^t)$ which is generated from observations made by all UAVs. The unnormalized probability map is calculated using Eq. (7), employing a recursive Bayesian estimation process described in Eq. (2) and incorporating non-detection likelihood information from $P(z_u^t = \bar{D} \mid v^t, r_u^t)$ [33, 44]. A detailed process for developing the expected value of the target detection time objective function can be reached in [28, 30].

$$ET(r_{1:U}^{0:t}) = \sum_{t=0}^{T} P(z_{1:U}^{1:t} = \bar{D} \mid r_{1:U}^{0:t}) = \sum_{t=0}^{T} \sum_{v^t \in N_x \times N_y} \tilde{b}(v^t) \tag{6}$$

$$\tilde{b}(v^t) = \prod_{u=1:\mathrm{U}} P(z_u^t = \bar{D} \mid v^t, r_u^t) \sum_{v^{t-1} \in N_x \times N_y} \tilde{b}(v^{t-1}) \tag{7}$$

Where, $\tilde{b}(v^0) =$ Initial probability map

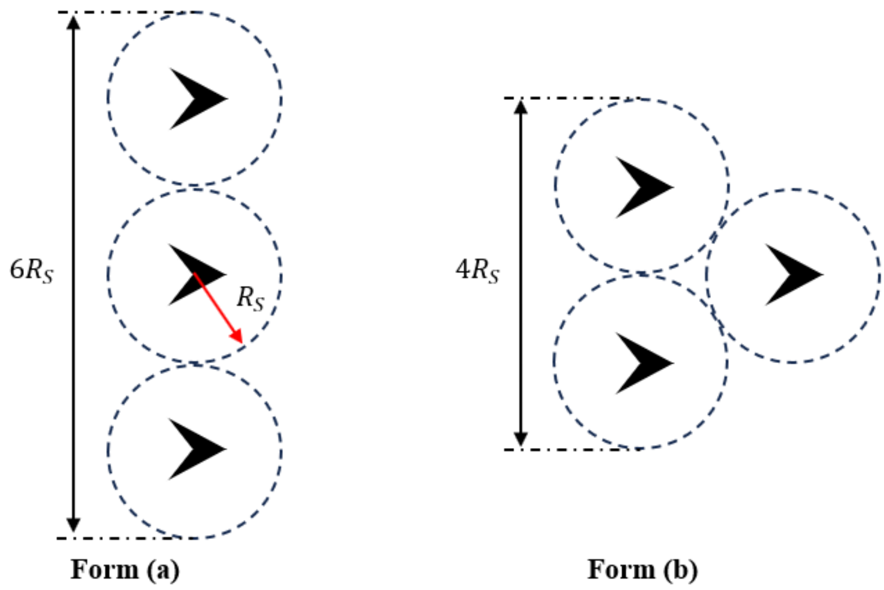


Fig. 2. The different positions of followers with respect to the leader

Where, T is the maximum horizon length (time). The *ET* function can only provide minimum time search paths, while the algorithm needs another objective function to determine the best formation of the UAVs to maximize coverage. To determine the coverage bandwidth (*CB*) of all UAVs, Eq. (8) has been formulated and utilized as the criterion. If we consider Form (B) in Fig. 2 as the scenario with the least search coverage, the bandwidth of the area covered by the followers specifically denotes the width of the region covered solely by the followers without any overlap with the leader's coverage area.

$$CB(r_{1:\mathrm{U}}^{0:t}) = \frac{4TR_S}{\sum_{u=1}^{U}\sum_{t=0}^{T} Bandwidth_u^t} \tag{8}$$

In general, by considering the same influence coefficient for *ET* and *CB*, the overall cost $J(r_{1:U}^{0:t})$ is obtained as follows:

$$J(r_{1:U}^{0:t}) = ET(r_{1:U}^{0:t}) + CB(r_{1:U}^{0:t}) \tag{9}$$

3- Optimization algorithm

In the MTS problem, various intelligent optimization algorithms have been used in different references. One such method is the ant colony algorithm, an intelligent metaheuristic optimization technique inspired by the pheromones and foraging behavior of real ants [45]. This method has the benefits of positive feedback, improved flexibility, robustness, and strong optimization capacity to tackle some different kinds of large and combinatorial optimization problems [46]. ACO had significantly provided acceptable results for extracting optimal solutions to the MTS problems in the presence of various constraints. In this optimization technique, a colony of artificial ants constructs, updates, and probabilistically follows potential solutions based on synthetic pheromone trails and heuristic input [21]. While ACO has been successful in solving discrete domains, it is not suitable for continuous domains. To address this limitation, an extension of the algorithm known as ACO_R was introduced [33], which incorporates relevant pheromone updates and solution construction processes aligned with ant-inspired algorithms. In ACO, a probability mass function and a pheromone table are utilized to handle discrete decision variables, while in ACO_R, a probability density function and an archive of solutions are employed for continuous decision variables [44]. Generally, the ACO_R uses all information to generate an archive and then uses this archive to construct solutions. A solution archive ($\mathcal{A}$) illustrated in Eq. (10) stores a collection of K best solutions (S_k, $k=1, 2, \dots, K$) as pheromone information in ACO_R. In each solution, N continuous decision variables are present (s^n, $n=1, 2, \dots, N$) that should be optimized in the optimization problem. All the solutions stored in the archive ($\mathcal{A}$) are sorted by their fitness rank. At the end of each iteration of the algorithm, the solution archive with a fixed and unchanged size is updated by adding new solutions and removing the worst ones [44].

$$\mathcal{A}: \quad \begin{array}{l} S_1 = \{s_1^1,\ s_1^2,\ \cdots,\ s_1^n,\ \cdots,\ s_1^N\} \\ S_2 = \{s_2^1,\ s_2^2,\ \cdots,\ s_2^n,\ \cdots,\ s_2^N\} \\ \vdots\ = \ \vdots\ ,\ \vdots\ ,\ \ddots,\ \vdots\ ,\ \ddots,\ \vdots \\ S_k = \{s_k^1,\ s_k^2,\ \cdots,\ s_k^n,\ \cdots,\ s_k^N\} \\ \vdots\ = \ \vdots\ ,\ \vdots\ ,\ \ddots,\ \vdots\ ,\ \ddots,\ \vdots \\ S_K = \{s_K^1,\ s_K^2,\ \cdots,\ s_K^n,\ \cdots,\ s_K^N\} \end{array} \tag{10}$$

The solution archive is used to model a probability density function for each variable (G_n, $n = 1, 2, \dots, N$) in the form of a Gaussian function with mean μ and standard deviation σ (Eq. (11)). For this problem, the mean for each G_n is equal to each variable in the solution archive ($\mu_k^n = s_k^n$), and the standard deviation is calculated using Eq. (12) [44].

$$G_n = \sum_{k=1}^{K} P_k \mathcal{N}(\mu_k^n, \sigma_k^n) \tag{11}$$

$$\sigma_k^n = \xi \frac{\sum_{r=1}^{K} \left(\mu_k^n - \mu_r^n\right)}{K-1} \tag{12}$$

Where ξ is a positive parameter to control the convergence speed of ACO_R. The large and small values for this parameter force the algorithm for high exploration and exploitation, respectively. The new solutions are selected according to a selection probability based on Eq. (13). Where w_k is the weight of the solution S_k, and is calculated according to Eq. (14) [33, 44].

$$P_k = \frac{w_k}{\sum_{k=1}^{K} w_k} \tag{13}$$

$$w_k = \frac{1}{qK\sqrt{2\pi}} e^{\left(\frac{-(k-1)^2}{2q^2K^2}\right)} \tag{14}$$

The parameter q in Eq. (14) is a selection pressure parameter that influences the solutions. Assigning $q = 0$ means only the best solution will be used for the generation of the new solution, and $q = \infty$ means all solutions have the same influence in generating the new solution.

4- Constraints

The planning of a trajectory in the presence of several constraints and optimization criteria is a critical aspect of the MTS problem. The optimization process has many constraints, especially for continuous MTS problems, so it's necessary to incorporate some of the conventional or new approaches to handling constraints. In this work, constraints including collision paths, communication, obstacle avoidance, dynamics, and kinematic characteristics are considered. Within this algorithm, we not only plan safe and flyable MTS paths for all UAVs but also consider adaptive formations to maximize coverage by all UAVs.

4- 1- Minimum time search constraint

In this study, the main constraint for returning search paths with minimal search time is the expected value of target detection time, as outlined in Eq. (6). Furthermore, since a complex optimization problem can greatly benefit from including problem-specific knowledge, in a similar strategy to [44, 47], we developed a heuristic function that uses a small group of ants in ACO_R to construct a part of the solution uniquely using information related to the optimization problem. This function selects the next waypoints aligned to cells with a high probability of the target's presence. By using this technique, the UAVs are directed toward the closest regions with the highest likelihood of having a target present. In addition, by defining the concept of maximum instant coverage based on Eq. (8), the algorithm planes search paths with an allowable wide bandwidth, which helps reduce search time.

4- 2- Kinematic constraints

The kinematic constraints of fixed-wing UAVs can have a significant impact on the solution of search missions. Fixed-wing UAVs face kinematic constraints due to their continuous motion and inability to hover. These constraints make it a challenge to design a flyable trajectory for this type of aircraft. Utilizing Dubins paths can address issues of flyability and curvature constraints when creating search paths for this type of aircraft.

It is proved by Dubins in [48] that a whole path containing straight lines and arcs with maximum curvature or minimum turn radius ($R_{\min}$, based on the kinematic constraint of the UAVs) is an optimal path between two points with different heading angles. The minimum turn radius for a fixed-wing aircraft with constant speed V and maximum bank angle (ϕ) under gravitational acceleration g is calculated as follows [49]:

$$R_{\min} = \frac{V^2}{g\sqrt{(load\ factor)^2 - 1}} \quad \text{where } load\ factor = \frac{1}{\cos\phi} \tag{15}$$

Using Dubins paths directly in the MTS problem has enabled the development of continuous search paths that meet the kinematic constraints of the fixed-wing UAVs at the lowest computational cost. For UAVs in a predefined formation, the minimum turn radius should be considered for all UAVs. For example, for a clockwise turn of the formation shown in Fig. 1, if the leader turns with $R_{\min}$, follower 1 and follower 2 have to turn with a smaller and larger turn radius, respectively. In this work, we tackle and ensure the kinematic constraint of all UAVs that fly in the formation with $\psi_{LF} = 90°$ (Form (A) in Fig. 2), and by considering $d_{LF} = R_{\min}$, the minimum turn radius of the leader for planning the Dubins path is set $2R_{\min}$. This radius for other formations can be calculated based on the azimuth angle of the follower, as follows:

$$R_{\min}^{Leader} = \frac{V^2}{g\sqrt{(load\ \ factor)^2 - 1}} + d_{LF}\sin(\psi_{LF}) \tag{16}$$

To satisfy the formation constraints, we developed a nonlinear three-degree-of-freedom simulation based on [36] alongside a formation flight strategy derived from [43]. The proposed MTS algorithm uses this simulator to generate the flyable path for followers based on the four constraints, including minimum and maximum safe distance, appropriate elevation, and azimuth angles between followers and leaders in a symmetrical form.

4- 3- Collision avoidance and communication constraints

In leader-follower formation flight, it is crucial for followers to maintain stable and real-time communication with the leader, while such communication is not necessary between followers themselves. Generally, the distance between any two UAVs must be greater than a safe distance (to avoid collision) and less than a specified fixed distance (to maintain communication). In this regard, we considered a fixed distance between each follower and leader equal to $2R_s$ ($d_{LF} = 2R_s$). Based on the formation flight rules, followers must adjust their speed to maintain this distance, which helps satisfy collision avoidance and communication constraints between leader and followers. To prevent collisions among followers, we also considered a minimum safe distance equal to $2R_s$ between the followers during reconfiguration. By assuming a symmetrical formation, it means the minimum azimuth angle (ψ_{LF}) is limited to 30°. This approach is summarized as follows:

$$\begin{cases} r_L^t - r_F^t = d_{LF} & ;\ \textit{For all followers during the entire flight time} \\ r_{F1}^t - r_{F2}^t \geq 2R_s \ \ or \ \ \psi_{LF} \geq 30^{\circ} & ;\ \textit{In the entire flight time} \end{cases} \tag{17}$$

Where, r_L^t and r_F^t are the positions of the leader and follower at the time t, respectively.

4- 4- Obstacle avoidance

In this study, UAVs are prevented from colliding with static obstacles by assuming the presence of initial information about them. Where, by defining a confidence area, the boundaries of the obstacles have been increased for the amount of R_s in all directions, and the planning algorithm avoids generating waypoints and paths inside this area. It is obvious that by defining the capability of the sensor of the UAVs to scan an area with a radius R_s, all regions near the obstacles can be searched by only one UAV on the border of the confidence area. In this regard, in each iteration of the algorithm, the generated flight path is checked for collision based on Eq. (18), and the path that cannot satisfy the obstacle avoidance constraint is ineligible and rejects the solution obtained in the MTS algorithm.

$$\begin{cases} \textit{Obstacle free path} & \textit{if} \ \ \{r_L^t \cup r_{F1}^t \cup r_{F2}^t\} \cap \{Obs \cup Conf\ \ Area\} = \varnothing \\ \textit{Ineligible} & \textit{Otherwise} \end{cases} \tag{18}$$

5- MTS in formation flight

This section proposes the MTS planner for a fleet of fixed-wing UAVs with one fixed leader and two followers in a symmetrical form. The key innovation of this planner lies in its ability to plan search paths that minimize the expected detection time while maximizing coverage for all UAVs in the optimal formation. To achieve this, the planner must account for various constraints such as the kinematics of fixed-wing aircraft, obstacle avoidance, collision avoidance, and communication simultaneously. In each step of the search mission, the proposed algorithm fine-tunes the position of the sequence of waypoints to generate the shortest possible search paths and also adjusts the azimuth angle of the followers to maximize the coverage of the environment. This algorithm is built upon the ACO_R approach with specific objective functions, comprising two main components: 1) constructing an archive in the form of Eq. (10) and 2) iteratively searching for the best outcome based on Eqs. (11) to (14) and the methodology detailed in section 3. Through a step-by-step planning process for waypoints and azimuth angles, the archive is formed for $N = 1$ as follows:

$$\mathcal{A}: \quad \begin{aligned} S_1 &= \{s_1^{waypoint},\ s_1^{azimuth}\} \\ S_2 &= \{s_2^{waypoint},\ s_2^{azimuth}\} \\ \vdots &= \ \ \vdots \quad , \quad \vdots \\ S_k &= \{s_k^{waypoint},\ s_k^{azimuth}\} \\ \vdots &= \ \ \vdots \quad , \quad \vdots \\ S_K &= \{s_K^{waypoint},\ s_K^{azimuth}\} \end{aligned} \tag{19}$$

Our methodology is based on the MTS-ACO_R algorithm proposed by Sara Perez-Carabaza et al. in [44], which we have adapted for the formation flight of UAVs. We extended this algorithm by using two parameters, the position of waypoints and the azimuth angle of followers, instead of focusing solely on the sequence of UAV actions over a fixed period. Additionally, we integrated the analytical Dubins

Algorithm 1: MTS in the formation flight

Inputs: Initial probability map $\tilde{b}(v^0)$, UAVs initial positions, ACO$_R$ Parameters (K, S, p, ξ, q)

1: **while** the target is not found **do**
2:   **while** generating an archive with a size K **do**
3:   Select a random distance from $4R_{\min}$ to $6R_{\min}$
4:   Using p percent of ants to find N_P heuristic waypoints for the next position of the leader (with the heuristic formation of the followers).
5:   Finding $K-N_P$ random waypoints and random azimuth angle, for the next position of the leader and for constructing formation flight in free space, respectively.
6:   Calculating the $R_{\min}$ for the leader based on Eq. (16) and planning Dubins path between the current position of the leader and other waypoints.
7:   Planning the flight path for all followers based on the simulation of the formation flight.
8:   Evaluating obstacle avoidance constraints for all planning paths and storing collision-free paths.
9:   **end while**
10:   Evaluating and sorting generated paths in the archive based on Eq. (9).
11:   **while** stop conditions are not met **do**
12:   **while** finding H feasible paths **do**
13:   Using p percent of the ants in each iteration to find N_H heuristic waypoint for the leader (with heuristic azimuth angle of the followers).
14:   Using Eq. (11) to Eq. (14) for generating $H-N_H$ (safe and flyable) new solutions (waypoints with related formation azimuth angles).
15:   Calculating the $R_{\min}$ for the leader based on Eq. (16) and planning Dubins path between the current position of the leader to the generated waypoints.
16:   Planning the flight path for all followers based on the simulation of the formation flight.
17:   Evaluate obstacle avoidance constraints for all planning paths and select collision-free paths.
18:   **end while**
19:   Merging and updating the previous archive with new solutions.
20:   Evaluate and sort all generated paths based on Eq. (9).
21:   Select K best solutions in the new archive.
22:   **end while**
23:   Return the information in the first row of the archive as the best next waypoint and azimuth angle
24:   Update belief based on the generated path and coverage area by all UAVs
25: **end while**
26: Return a sequence of waypoints and flyable MTS flight path with the best formation for maximum coverage by UAVs

path planning method into this algorithm to increase its convergence speed. The pseudocode and flowchart of the proposed approach are shown in Algorithm 1 and Fig. 3, respectively. The algorithm builds MTS paths iteratively by employing a group of UAVs in an adaptive formation flight to locate the target. It consists of two main sections: generating an archive (lines 2 to 9) and the main ACO$_R$ loop (lines 11 to 22). As mentioned before, p the percentage of the initial solutions in archive $\mathcal{A}$ ($N_P = p.K$) is obtained based on the MTS heuristic information (line 4). In this regard, the waypoints are selected at a random distance (between $4R_{\min}$ to $6R_{\min}$) and aligned to cells with a high probability of the presence of the target; moreover, by assuming the optimal configuration as Form (B) in Fig. 2, the heuristic value for azimuth angle is considered equal to 30°. It is obvious that to fulfill the generating archive $K-N_P$ random waypoint with

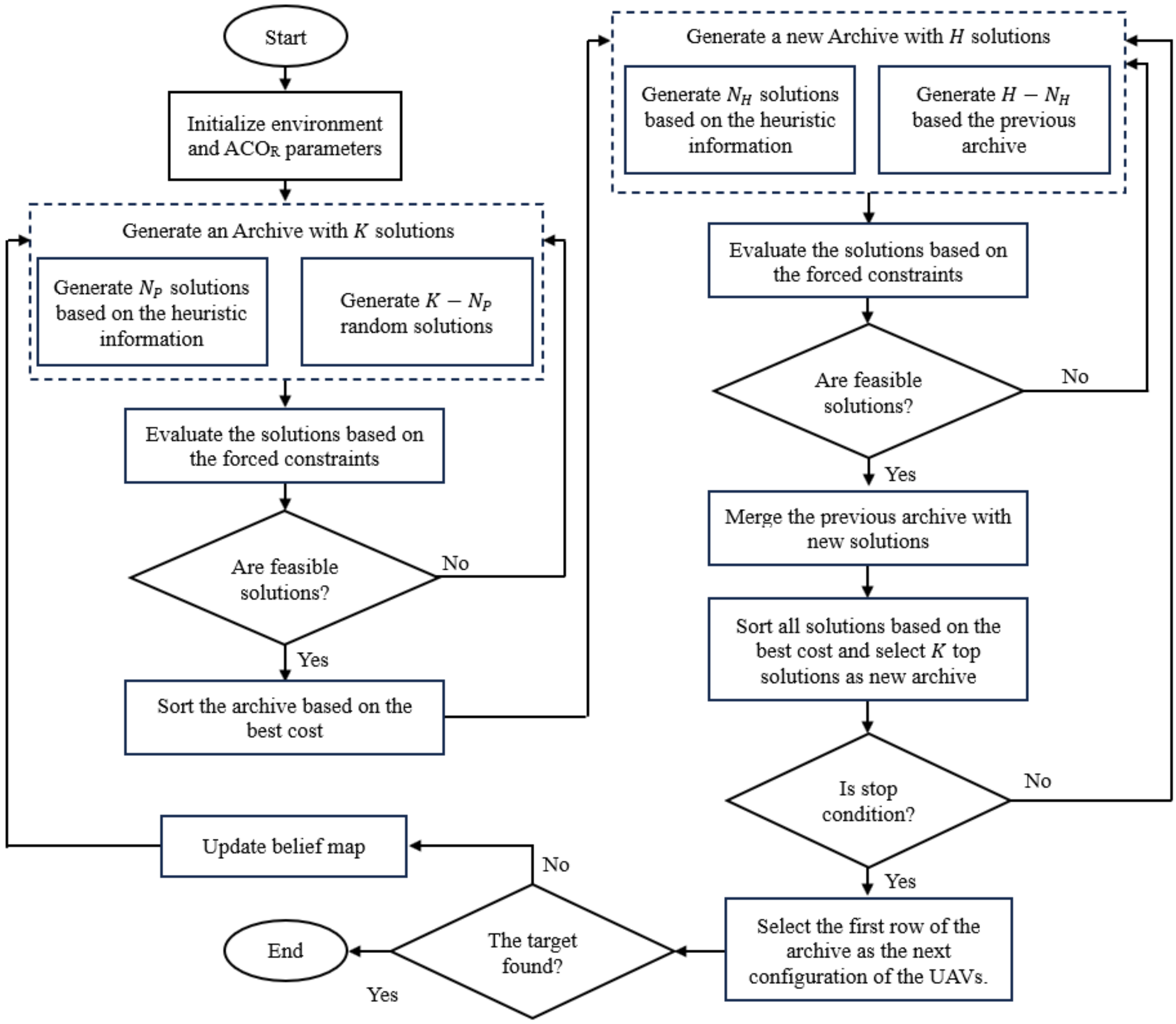


Fig. 3. The flowchart of the MTS in the formation flight algorithm

random azimuth angles should be generated (line 5). In the next step, after calculating $R_{\min}$, the flyable path of the leader is generated using the Dubins method based on the kinematic constraints of the UAVs (line 6). After planning the flight path of the leader, the flight paths of the followers are obtained through a nonlinear three-degree-of-freedom simulation (line 7). Finally, in line 8, the flight paths must be evaluated from the point of view of not encountering obstacles based on Eq. (18). After completing the archive, it is sorted in line 10 based on Eq. (9).

The main ACO$_R$ loop utilizes an iterative process until a stop condition is met. Within this loop, for affecting the new solutions with heuristic information, similar to line 4, p the percent of the new solution population, H, ($N_H = p.H$) is obtained based on the MTS heuristic information (line 13). Immediately after, within each ACO$_R$ iteration, in line 14, $H - N_H$ new solutions are generated based on the archive and the process outlined in section 3. The algorithm repeats the process from lines 6 to 8 for the new solutions in lines 15 to 17. After completing the inner loop of the algorithm, the new solutions are merged with the previous archive. The new archive is then sorted using Eq. (9) in line 20, and the top K solutions are selected to update the archive for the next iteration in line 21. When the main algorithm's stop condition is met, the first member of the archive is chosen as the new waypoint for the leader and the optimal azimuth for followers in for new formation (line 23). This step is the final step for one segment of the search path. By flying the UAVs on the planned paths and searching the environment, the belief map can be updated based on Eqs (2) and (4) and information gathered and shared by all UAVs (line 24). The mentioned steps will continue until the algorithm finds the survivor (as a target) as a termination condition.

Table 1. The performance parameters of the UAVs

Parameter	Value	Unit
V	57	m/s
Maximum bank angle (ϕ)	33	deg

Table 2. The parameters of the initial probability map

Region	a'_k	b'_k	c'_k	d'_k
1	15	15	1	0.7
2	15	5	3	0.3

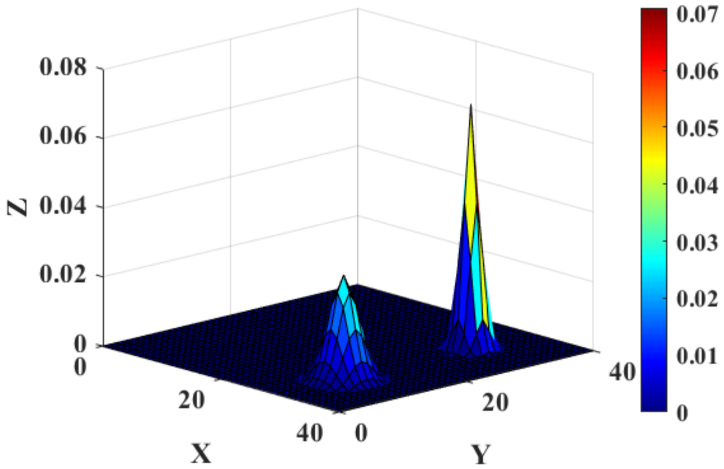


Fig. 4. Three-dimensional view for a discretized initial probability map

6- results

In this study, due to the absence of real flight-testing capabilities and the benchmarking test data, we have simulated the search mission for various complex scenarios. Statistical analysis is conducted to assess the effectiveness of the proposed algorithm. For this purpose, a two-dimensional area of $20\ \text{km} \times 20\ \text{km}$ is designated as the search environment, and three identical long-endurance surveillance fixed-wing UAVs with similar functionalities and performance constraints as outlined in Table 1 are chosen to carry out the search missions. To prepare the target probability map, this area is discretized into a 40×40 cell and the model for target presence is considered with a Gaussian distribution function as follows:

$$P_{i,j\in N_x\times N_y}(v^0)=\frac{\sum_{k=1}^{Q} d'_k e^{-\left[\frac{(i-a'_k)^2+(j-b'_k)^2}{c'_k}\right]}}{\sum_{i,j=1}^{N_x\times N_y}\sum_{k=1}^{Q} d'_k e^{-\left[\frac{(i-a'_k)^2+(j-b'_k)^2}{c'_k}\right]}} \tag{20}$$

Where, Q is the number of target presence regions and a'_k, b'_k, c'_k, and d'_k are some parameters for the defined probability regions. As an example, the initial probability map with the parameters mentioned in Table 2 is shown in Fig. 4. In this case, two areas are assumed to be high-probability regions, where cells with warmer colors are more likely to contain the target.

As a means of illustrating the algorithm's capabilities, two predefined scenarios have been designed as follows:

Scenario I: Search a free obstacle region with two different high-probability areas for the presence of the target.

Scenario II: Search for a static target in a region with obstacles and a narrow safe corridor.

In both scenarios, all UAVs are assumed to be aware of the details of the mission environment, including the precise locations of obstacles and the probable regions of the targets. This information is used to create an initial probability map for the MTS algorithm. We considered a sample of long endurance surveillance-class of UAVs as a case study to simulate and prove our proposed algorithm. UAVs in this category typically have limited agility and maneuverability. By assuming a UAV with performance characteristics

Table 3. The setting parameters of the search algorithm for scenario I

Parameter	Value
K	50
H	20
ξ	0.1
q	0.1
P	10
N	5
Number of iterations	30

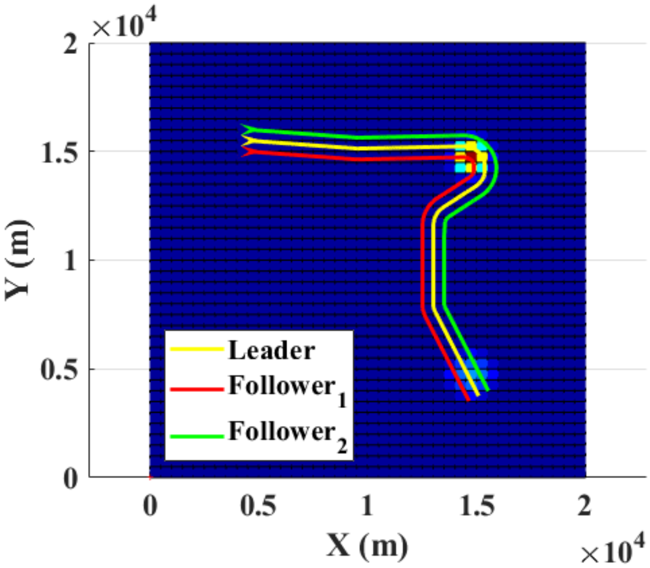


Fig. 5. The UAVs search paths for scenario I

outlined in Table 1, we can calculate the minimum turn radius based on Eq. (15) as follows:

$$load\ factor = \frac{1}{\cos(33)} \simeq 1.2 \quad \rightarrow \quad R_{\min} = \frac{57^2}{9.81\sqrt{1.2^2 - 1}} \approx 500 \text{ m} \quad (21)$$

Based on Eq. (21), the minimum turn radius of 500 m is considered for all UAVs in both scenarios. In addition, we assumed that all UAVs are equipped with the same sensors, and the radius of the detection sensor disk is equal to 250 m.

6- 1- Evaluation of the MTS in the formation flight algorithm to consider the priority of the search based on scenario I

This scenario considered a search mission in an obstacle-free region with two different high-probability areas for the presence of the target. Ideally, the UAVs should thoroughly search all areas with a likelihood of containing the target, giving priority to those with higher probabilities. The scenario does not include a stop condition for finding the target; instead, a planner horizon of $N = 5$ is set, meaning the search process stops after planning five path segments. Three homogeneous fixed-wing UAVs started the search mission from the start locations in an initial symmetrical formation ($\psi_{LF_0} = 90°$). The parameters K, H, ξ, q, P and the maximum iteration of the algorithm are set according to Table 3 for this specific scenario. Fig. 5 and Fig. 6 depict the search paths and several evaluation graphs to examine the performance of the proposed method. Fig. 5 shows how the algorithm constructs the search path by prioritizing high-probability areas. UAVs are depicted searching first for areas with a high probability, and then for areas with a low probability. Fig. 6 (a) demonstrates that the algorithm planned the formation of the UAVs to cover the maximum ground area along the entire search path, in the absence of any obstacles. Figs. 6 (b), 6 (c), and 6 (d) demonstrate the algorithm's capability to maintain UAVs in a planned formation. It is shown in the entire search of Dubin paths that followers maintain a safe distance from the leader ($\varepsilon_{d_{LF}}$), and minimal deviation from $\psi_{LF} = 90°$ and $\theta_{LF} = 0°$.

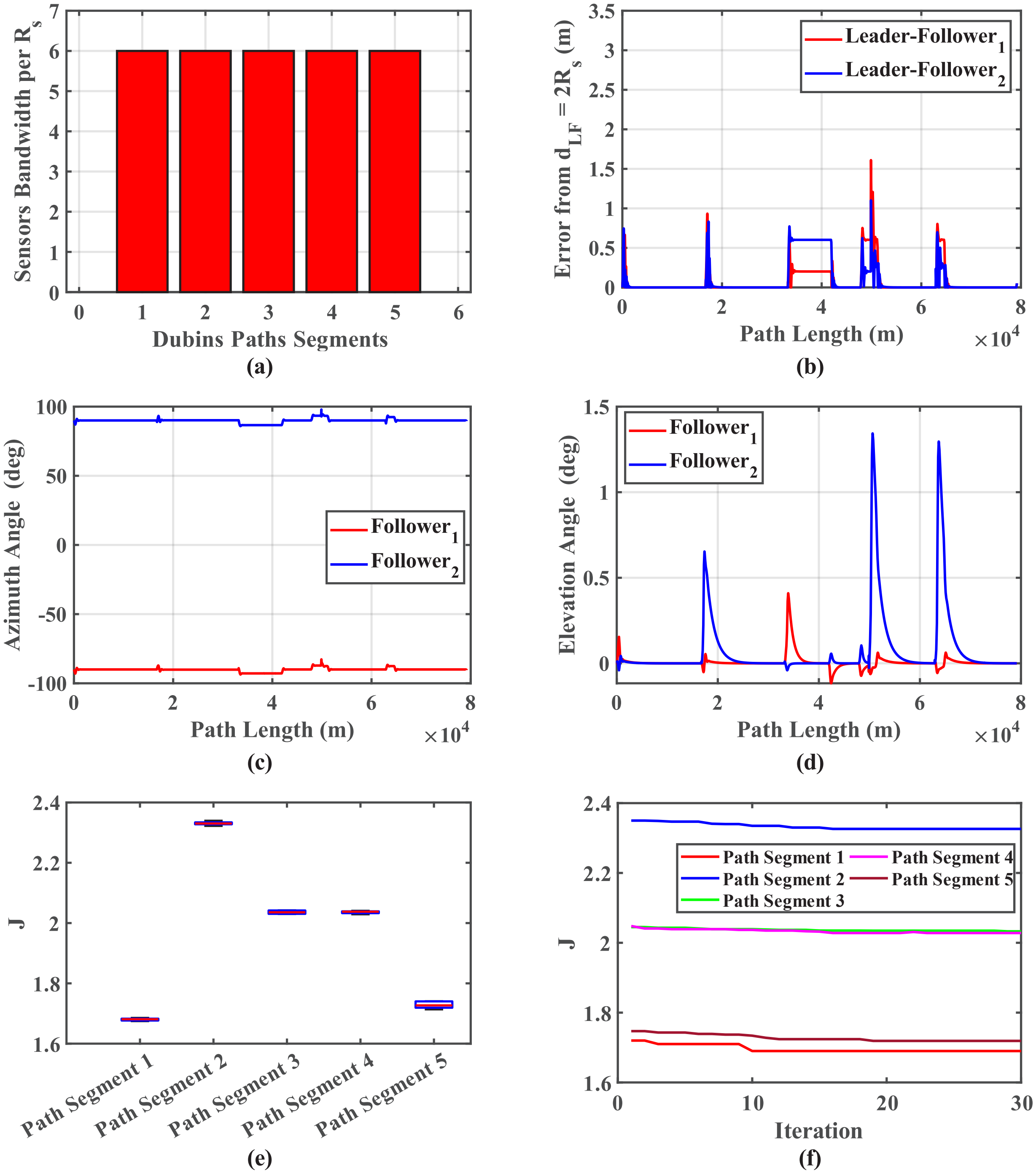


Fig. 6. The evaluation graphs for scenario I

Fig. 6 (e) presents a statistical graph showing the overall cost of each Dubin path segment, where each box represents the range of changes in this parameter over all iterations of the ant colony algorithm. Fig. 6 (f) indicates the convergence trend of the optimization process. It is evident from all parts of the path that the proposed algorithm converges to final values within fewer than 17 iterations. In summary, this scenario shows that the proposed algorithm provides a fast path planning approach that is both effective and flexible in handling search missions by prioritizing search regions and ensuring maximum coverage.

Table 4. The setting parameters of the search algorithm for scenario II

Parameter	Value
K	80
H	30
ξ	0.2
q	0.1
P	20
N	5
Number of iterations	40

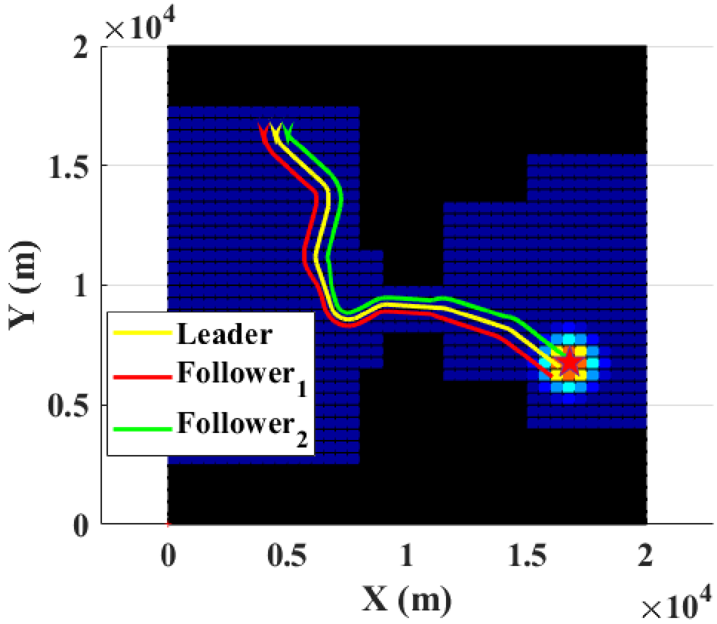


Fig. 7. The UAVs search paths for scenario II

6- 2- Evaluation of the reconfiguration formation flight capability for MTS in the presence of static obstacles based on scenario II

To assess the effectiveness of the proposed algorithm for searching in the presence of obstacles, a scenario for searching in an environment with known strict static obstacles has been designed. In this scenario, the algorithm controlled the formation of the UAVs in free-obstacle regions by changing the azimuth of the followers to plan a safe search path. In a similar way to the previous scenario, three fixed-wing UAVs started their search missions from the start locations in a symmetrical formation ($\psi_{LF_0} = 90°$). The assumption is that the survivor (target) is in the center of the high-probability region, and once one of the UAVs locates it, the search will end. The parameters K, H, ξ, q, P and the maximum iteration of the algorithm for this scenario are set according to Table 4.

Fig. 7 and Fig. 8 show the planned search paths and evaluation graphs for scenario II, respectively. The black cells in Fig. 7 represent the regions occupied by static obstacles. This figure shows the capability of the algorithm to find a safe search path toward the target. Fig. 8 (a) shows that the algorithm can find a safe path through the narrow corridor between the obstacles by changing the formation of the UAVs. To avoid collisions with obstacles along certain parts of the planned path, the UAVs incurred penalties affecting their search bandwidth. An analysis of Figs. 8 (b), 8 (c), and 8 (d) reveal that the algorithm has been successful in maintaining the formation of the UAVs with minimal deviation. The statistical graph in Fig. 8 (e) exhibited the variance of the search cost for each segment of the Dubins path during all iterations of the algorithm. In some path segments, it is evident that all iterations have converged to a limited cost (J) due to the limitation of free-obstacle space.

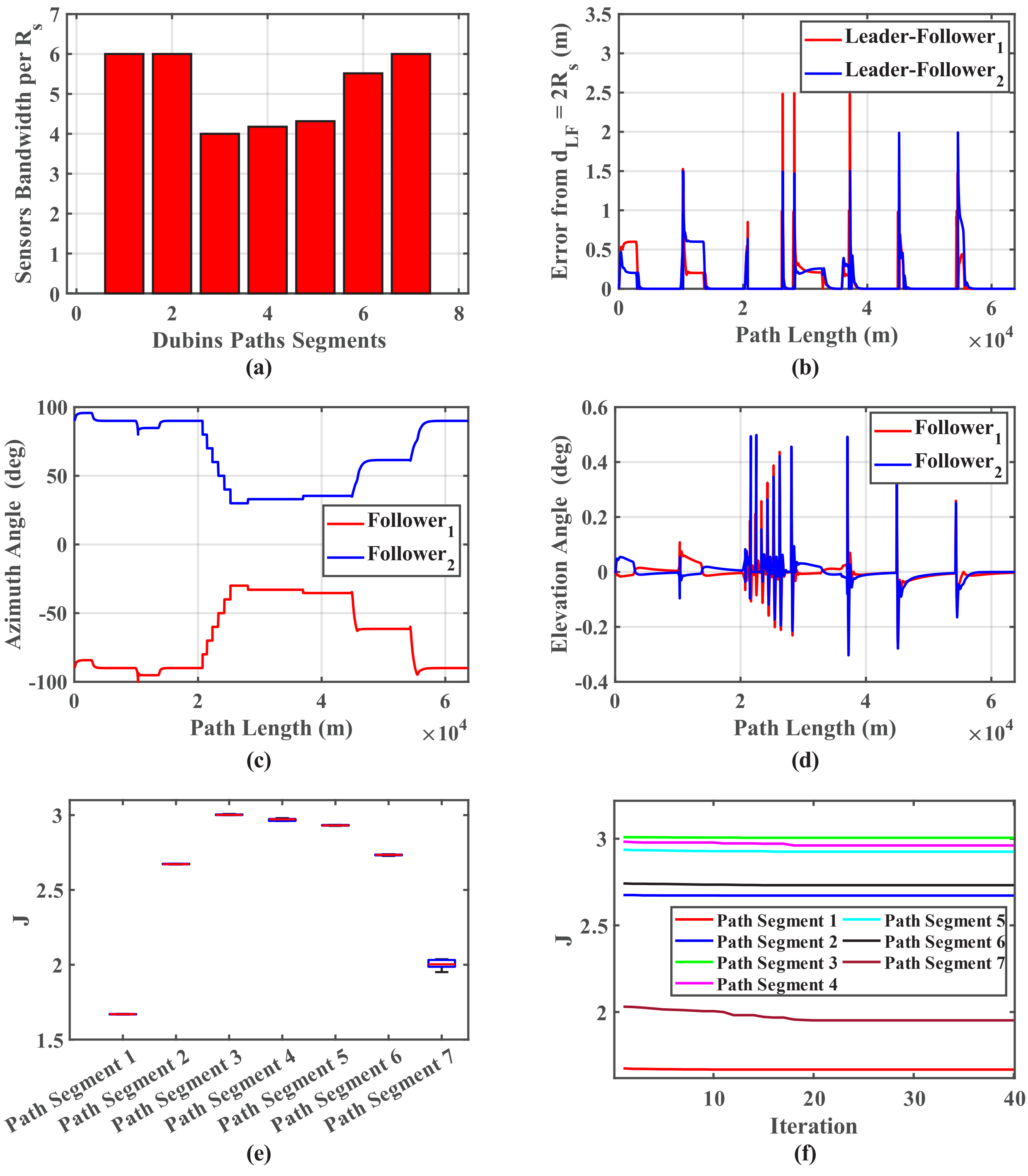


Fig. 8. The evaluation graphs for scenario II

Fig. 8 (f) shows the convergence trend of the optimization process for all segments of the search path. It is clear that the use of problem-specific heuristic functions has been highly beneficial in achieving a fast search algorithm. The evaluation of the obtained results proves that the proposed algorithm is capable of finding safe search paths for a group of UAVs among strict obstacles.

6- 3- The Monte-Carlo simulation

The continuous ACO and proposed MTS have a stochastic nature, and since the convergence of different statistical analyses can confirm the effectiveness and performance of our proposed methods, Monte-Carlo simulation experiments were conducted for both search scenarios. This is done by running each scenario 20 times to ensure robustness in the

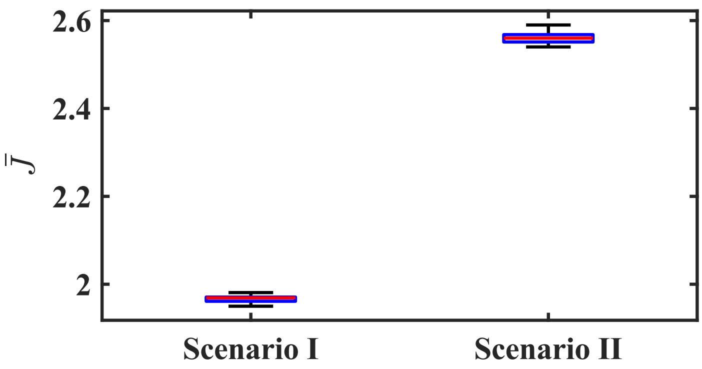


Fig. 9. The result of Monte-Carlo simulation experiments

Table 5. The setting parameters of the PSO search algorithm for scenario II

Parameter	Value
Swarm Size (population)	80
Iterations	40
Inertia weight	1
Inertia weight damping ratio	0.99
Personal learning coefficient	1.9
Global learning coefficient	2

results. To evaluate the results of this test, a statistical diagram is drawn to show the variance of the average search cost for all path segments ($\bar{J}$) in each run. It is shown in Fig. 9 that the algorithm consistently has converged on paths with nearly identical costs across multiple runs of fixed scenarios.

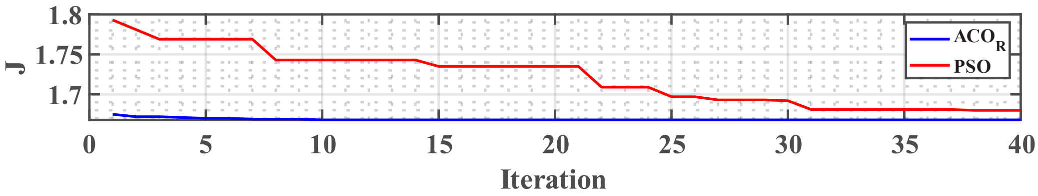
6- 4- Comparison of the MTS-ACO$_R$ in the formation flight with another optimization algorithm

Using heuristic information in MTS problems can lead to a significant improvement in the search results. It has been proven in [28, 30, 32, 44] for the MTS problem that the ACO and ACO$_R$ are superior to some other optimization methods, such as cross-entropy optimization, bayesian optimization algorithm, and genetic algorithm when heuristic information is available. To assess the efficacy of the proposed MTS problem in the configuration of a formation flight with heuristic information, in this section, we replaced the optimization method of our search algorithm (Algorithm 1) with the Particle Swarm Optimization (PSO) method [50] and executed the algorithm for scenario II under the same conditions. The parameters for the PSO algorithm were initialized using the values in Table 4 for the proposed MTS problem. The comparative outcomes based on the objective function calculated using Eq. (9) are shown in Fig. 10. The presented graphs for all the path segments of scenario II show that the proposed algorithm by utilizing ACO$_R$ and heuristic information has achieved the optimal values in significantly fewer iterations and less computation time than PSO. The comparison results indicate that the developed MTS algorithm is more advantageous than a conventional meta-heuristic optimization algorithm for searching a target in the configuration of symmetrical formation flight of multiple UAVs.

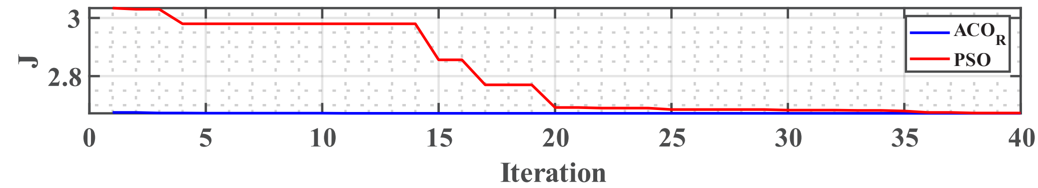
6- 5- Discussion

The simulation and comparison presented in the previous sections demonstrate that the MTS-ACO$_R$ algorithm effectively plans minimum-time search paths for multiple fixed-wing UAVs with adaptive formation. Despite the efficiency of the developed algorithm, there may be challenges that must be considered for implementing the proposed algorithm in real-world scenarios as follows:

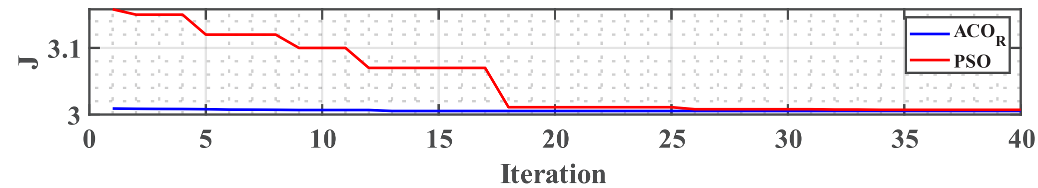
The proposed algorithm relies on stable communication links and reliable target detection sensors that continuously observe the earth's surface. Any faults or uncertainties in these components could impact the algorithm's performance. Redundancy in sensors and communication links or utilizing the algorithm's capability to remove faulty agents from the formation can mitigate this issue.



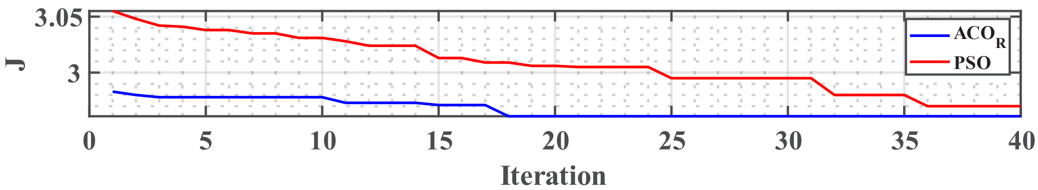
(a) Path Segment 1



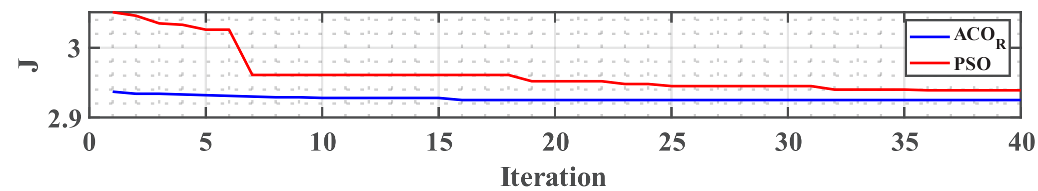
(b) Path Segment 2



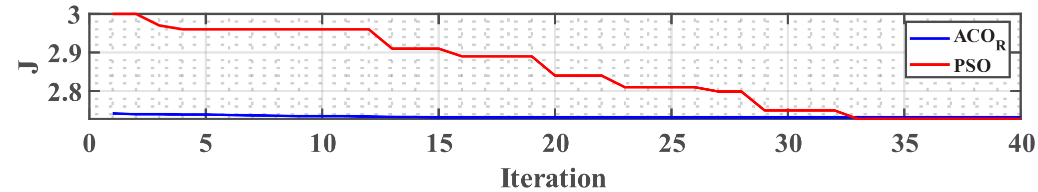
(c) Path Segment 3



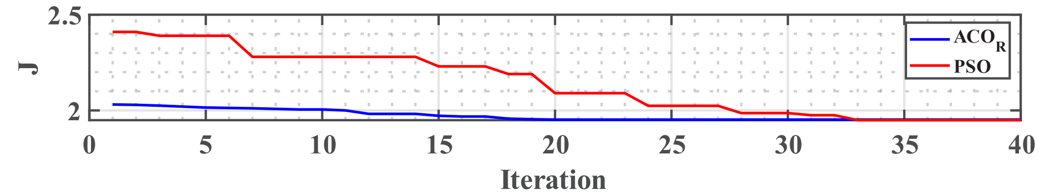
(d) Path Segment 4



(e) Path Segment 5



(f) Path Segment 6



(g) Path Segment 7

Fig. 10. Comparison of the MTS in the formation flight by utilizing ACOR and PSO

Atmospheric disturbances are inherent in real environments. Ground-based equipment, such as cup anemometers and more sophisticated remote sensing techniques, is commonly utilized to detect hazards and no-fly areas with adverse turbulences before a mission commences. By using this information, the proposed algorithm will be able to identify these regions as no-fly areas (similar to static obstacles) that UAVs should avoid. However, the existence of undefined and unknown hazardous turbulent regions, especially in mountainous environments, may pose a threat to the safety of the UAVs and the search mission. Therefore, equipping UAVs with real-time onboard detection systems and integrating wind estimation methods with the MTS-ACO_R algorithm can be a challenge for search in real-world scenarios.

In most search and rescue operations, such as searching for survivors after natural disasters or searching for missing persons in remote forests or wilderness areas, the search environment, including obstacles and targets, is either stationary or the rate of change is significantly lower than the speed of UAVs. Our proposed algorithm also considers this assumption for the environment and developed an efficient MTS search method for searching in the configuration of adaptive formation of multiple fixed-wing UAVs. In special cases where obstacles or targets have a higher speed than UAVs, UAVs may need sensors to detect dynamic obstacles, and the algorithm may need to consider the dynamics of the target in updating the target probability map. The integration of all these complex factors into the proposed MTS-ACO_R algorithm could lead to an improvement in search accuracy, but it would also increase computational time and require UAVs with powerful processor units. It could be a potential challenge for the designer to balance complexity, cost, and accuracy to develop a practical solution applicable to various UAV platforms.

7- Conclusions

In this study, we addressed the challenge of minimizing search time for a reconfigurable symmetric leader-follower formation of fixed-wing UAVs. Our proposed algorithm utilized continuous ant colony optimization to determine optimal search paths and flight formations for multiple UAVs, maximizing instantaneous coverage. By optimizing both the position of waypoints and the azimuth angle of followers relative to the leader, we were able to achieve efficient minimum-time search paths. The use of adaptive azimuth angles for followers has made algorithms more efficient in planning search paths in environments with strict obstacles. The proposed algorithm for planning each segment of the search path has used heuristic information, based on the initial information from the environment and the knowledge gained from observations and data made by UAVs, to generate solution archives during the optimization process. A comparison between our approach and a conventional meta-heuristic optimization algorithm (PSO) has demonstrated the effectiveness of this approach in achieving a fast search algorithm.

This study also introduced an approach for using an analytical Dubins method (with low computational time) to plan a safe and feasible minimum-time search path for the leader. Additionally, it integrated a leader-follower formation strategy with the main algorithm to accurately plan flight paths for the followers based on several key imperative constraints. The simulations and statistical analysis of different scenarios have confirmed the accuracy of the proposed algorithm in adapting and maintaining the formation of the UAVs to find the search paths in the shortest time in an environment with static obstacles.

In future work, this study can be developed for dynamic environments with multiple dynamic survivors. Moreover, the planner can be more flexible in adjusting to complex three-dimensional environments by extending the algorithm to the asymmetrical formation of UAVs. In this regard, adding other optimization factors, such as the velocity of the UAVs, as well as uncertainty factors related to target detection sensors and communication links, would be an interesting research line.

Nomenclature

$\mathcal{A}$	Solution archive
b	Belief map
CB	Coverage bandwidth
$Conf$	Confidence area
d	Distance between two UAV
D	Detection of the target
$\bar{D}$	Non-detection of the target
a'_k, b'_k, c'_k, and d'_k	The modeling parameters for probability regions.
ET	Expected value of target detection time
g	Gravitational acceleration
G	Probability density function (Gaussian function)
H	The population size of new solutions
J	Objective function
N	The number of decision variables
$N_x \times N_y$	The size of the grid map
Obs	Obstacle
p	The percentage of the initial solutions in the archive
P	Probability distribution function (PDF)
q	Selection pressure parameter
Q	The number of target presence regions
r	Location of the UAV
$R_{\min}$	Minimum level turn radius
R_s	The radius of the detection sensor disk
s	Decision variables
T	Maximum horizon time
v	Target existence probability in each cell
V	Airspeed
w	Weight of solution S
x, y	UAV's horizontal position in the body frame
X, Y	The frames' first and second axes
z	Sensor measurements
Greek symbols	
γ	Flight path angle
θ	Elevation angle
μ	Mean
ξ	Parameter to control the convergence speed of ACO_R
σ	Standard deviation
χ	Heading angle of the UAV
ϕ	Maximum bank angle
ψ	Azimuth angle

Subscript

F	Follower
I	Inertial frame
K	Archive size
l	Local frame
L	Leader
u or U	UAV

Superscript

t	Time

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