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Evolutionary Planning of Multi-UAV Search for Missing Tourists

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ABSTRACT In recent years, there have been increasing reports of missing tourists around the world. The use of unmanned aerial vehicles (UAVs) can significantly improve the performance of search and rescue operations. However, planning the search paths of UAVs can be a highly complex optimization problem, and one of the most challenging tasks in the problem formulation is the estimation of target location probability distribution over time. This paper presents a problem of scheduling multiple UAVs to search for missing tourists and proposes a method for estimating tourist location probabilities which change with topographic features, weather conditions, and time. To solve the problem efficiently, we propose a hybrid evolutionary algorithm which consists of the main algorithm and a sub-algorithm. The main algorithm uses specific migration and mutation operators to evolve a population of main solutions, and the sub-algorithm combines a problem-specific heuristic and tabu search method to optimize each UAV path. The experimental results on a wide variety of test instances (including five real-world instances) demonstrate the performance advantages of the proposed method.

INDEX TERMS Unmanned aerial vehicle (UAV), path planning, discrete-time optimization, evolutionary algorithms.

I. INTRODUCTION

In recent years, there has been an increasing number of tourists (including many so-called ‘‘tour pals’’) going missing when they crossing unmanned areas without approval. Based on incomplete statistics from the National Tourism Administration of China, during 2008-2017, over 1,600 tourists have been reported missing in the country, among which 76% were rescued, 6% unfortunately lost their lives, and the remaining 18% are yet to be found, as summarized in Fig. 1. A lot of human and material resources have been invested in search and rescue operations. Such operations can greatly benefit from the use of unmanned aerial vehicles (UAVs) owing to their advanced sensing functionality, flexibility, and autonomy. For instance, in Jan 2017, Australian water police used an Eagle-3 UAV to locate two missing tourists in Ku-ring-gai Chase National Park within one hour. On May 2, 2018, two UAVs launched by the local police took about two hours to detect a graduate student with whom contact had been lost two days before in Taibai Mountain, China.

UAV search problems, including those utilizing a single UAV or multiple UAVs to search for static or dynamic targets, have been studied extensively [1]. Early studies mainly employ local search methods such as those that always choose the next step with the largest payoff [2]–[5] or always follow a systematic offset path without leaving large holes or overlaps [6], [7]. Such methods are easy to implement and efficient in small-scale operations, but often lead to poor search performance in large-scale operations. More recent studies have considered UAV search as a global optimization problem with the objective of minimizing the expected detection time or maximizing the detection probability accumulated over the whole operation [8]. However, even for the case of a stationary target and a single UAV, such a search problem is known to be NP-hard [9], and hence traditional optimization methods will be prohibitively time-consuming for large-size instances. Besides, most methods require that the prior probability distribution of the target location over

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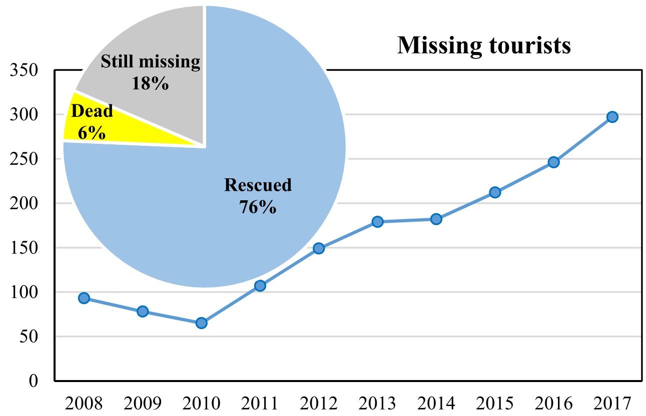


FIGURE 1. Incomplete statistics of reported missing tourists in China during 2008–2017 (the broken line) and the results of search-and-rescue operations (the pie chart).

the search area is known. Nevertheless, it is not a trivial task to estimate the probability distribution, and thus it can be very difficult to adapt a method that is efficient in a particular scenario to other similar or different scenarios.

Motivated by experiences from many real-world search-and-rescue operations, in this paper we formulated a problem of multi-UAV path planning for searching for missing tourist as a permutation-based, discrete-time optimization problem. As a key part of the problem formulation, we propose a method for estimating the probabilities of tourist location which change with topographic features, weather conditions, and time. To solve the highly complex combinatorial optimization problem, we propose a hybrid evolutionary optimization method that consists of a main algorithm for evolving a population of candidate solutions to the problem, and sub-algorithm for optimizing the path of each UAV in the solutions. Computational experiments demonstrate that the proposed method exhibits significant performance advantages over other popular methods on a wide variety of test instances and real-world instances of the problem. The main contributions of this paper can be summarized as follows:

- We formulate a new UAV search problem for minimizing the expected time of detecting missing tourists based on time-varying distribution of tourist location probabilities. This problem is more practical than many existing ones in UAV search operations.
- We propose a practical method for estimating the probabilities of tourist location over time, which plays a key role in the problem formulation and can be used in many other similar problems. To our knowledge, this is the first method that providing practical procedures for estimating the probability distribution of a missing target in a search region based on target information and topographical and weather conditions in a relatively accurate manner.
- We propose a new hybrid evolutionary algorithm for the problem, which exhibits competitive performance compared to the state-of-the-art. In particular, the results on some real-world instances show that our method can provide a significant improvement to life-critical operations.

The remainder of this paper is structured as follows. Section II introduces related work. Section III presents the UAV search problem. Section IV describes the hybrid evolutionary algorithm in detail. Section V presents the computational results, and Section VI concludes with a brief discussion.

II. RELATED WORK

Early studies on UAV path planning for search-and-rescue tasks mainly employ greedy methods (such as lookahead search which always chooses a region with the maximum probability of finding the target [3]–[5]), contour search methods (such as spiral search and potential field search which follow offset paths in a highly systematic fashion without leaving large holes or overlap [6], [10]), and their variants and combinations [3], [6], [7], [11]. Such methods are relatively easy to implement, but they do not use an objective function measuring the overall search performance of the whole operation, and thus often perform poorly in large-scale search operations.

More recent studies have considered UAV path planning as a global optimization problem for maximizing a performance measure (such as the expected detection time or detection probability) accumulated over the whole operation. To efficiently solve such a complex problem, numerous problem-specific heuristic methods and meta-heuristic methods have been proposed. The former includes the goodness ratio heuristic [8], Monte Carlo tree search [12], improved coverage search with geometric relations [13], expanding neighborhood search technique [14], etc. However, problem-specific heuristics have limited extensibility, and they are easily trapped in local optima.

The latter includes various nature-inspired algorithms or evolutionary algorithms, which have aroused more interest because they are capable of obtaining optimal or near-optimal solutions within an acceptable time by evolving populations of candidate solutions to simultaneously explore multiple regions in the solution space [15], [16]. Lin and Goodrich [17] proposed two genetic algorithms (GAs) for a UAV search problem with the objective of maximizing the detection probability accumulated in 2-D space. The first GA employs a string of directions (i.e., north, east, south, and west) and the second employs a sequence of node positions for path encoding. They showed that the two GAs are much faster than a local hill climbing algorithm and a complete-coverage algorithm. van Willigen *et al.* [18] proposed a particle swarm optimization (PSO) algorithm to generate a pre-planned UAV path for missions that involve searching and identifying targets. The path can be adapted at runtime based on the information acquired during the remainder of the mission. For UAV search-and-rescue in post-disaster assessment, Heidari and Abbaspour [19] proposed a bacterial foraging algorithm (BFA) which exhibited good robustness on test instances. Zhang and Duan [20] formulated a global UAV route planning problem as a constrained optimization problem in 3-D environments, and proposed for the problem a constrained differential evolution (DE) algorithm that outperforms many existing constrained optimization algorithms on the test set. Considering a problem of UAV path planning to locate a lost target in the minimum possible time, Perez-Carabaza et al. [21] proposed an ant colony optimization (ACO) algorithm that combines the learning capabilities of the pheromone trails left by good UAV paths with a problem-specific heuristic. Their results showed that the ACO outperforms some minimum-time-search heuristics and the GAs presented in [17]. Yang and Yoo [22] proposed a hybrid GA and ACO algorithm for optimizing UAV paths to maximize the value of gathered sensing information and minimize the total cost in terms of flying time, energy consumption, and operational risk. Recently, Zheng *et al.* [23] studied a collaborative human-UAV search problem, the objective of which is to minimize the expected time at which the target is reached by human searchers. They proposed a discrete optimization algorithm based on biogeography-based optimization (BBO) which exhibited competitive performance compared to other popular metaheuristics. In [24] Wang et al. proposed a hyper-heuristic that integrates different individual metaheuristics and adaptively invokes them based on real-time feedback. Simulation results showed that the hyper-heuristic outperforms each individual metaheuristic.

It is worth noting that almost all existing UAV path planning methods for target search require that the prior probability distribution of the target location is known. However, the probability distribution estimation can be very difficult, which severely limits the adaptation of such methods from one scenario to another.

III. PROBLEM

A. PROBLEM INPUTS

The problem considered in this paper is to use a set of n UAVs to search for missing tourists in a wide area such as a natural reserve or a geological park. For simplicity, we first assume there is one tourist (or a group of tourists who move together). However, as will be described later, the problem formulation can be easily extended to cases with multiple tourists dispersed in the search region. The search region A is divided into m subregions $\{a_1, a_2, \ldots, a_m\}$ based on the topographic features. We use a_0 to denote the subregion in which the tourist was last seen, $a_{j,0}$ to denote the initial location of UAV j, and d_i to denote the distance from a_0 to subregion a_i. The target location is unknown, but we can estimate a prior probability $p_t(i)$ of target location in each subregion a_i at time t ($i = 1, 2, \ldots, m$; $t = 0, 1, \ldots, T$), where 0 denotes the initial time and T is the maximum allowable time of the operation. In the next subsection, we will discuss the details on location probability estimation.

If the tourist is located in subregion a_i at time t, then we can also estimate the posterior probability $\rho_t(i, j, k)$ that he/she will be detected by UAV u_j searching the subregion with mode k at t ($0 \le t \le T$; $1 \le i \le m$; $1 \le j \le n$; $1 \le k \le K$). Here K denotes the number of search modes of the UAVs. The more detailed the search mode, the higher the detection probability, but the more search time required. In subsection III-C, we will discuss more details on UAV search modes and detection probability.

We are also given the time $\Delta\tau(i, j, k)$ required by UAV u_j to search subregion a_i with mode k, and the time $\Delta t(i, i', j)$ for UAV u_j to fly from a subregion a_i to another $a_{i'}$. This formulation allows UAVs to have different detection abilities and different flight speeds. In many real-world operations, the UAVs are identical, and hence the variable notations can be simplified to $\rho_t(i, k)$, $\Delta\tau(i, k)$ and $\Delta t(i, i')$.

B. LOCATION PROBABILITY ESTIMATION

By analyzing the travel paths of numerous tourists, we propose a method for location probability estimation based on the information of the tourist and search region. In our practice, given a search region, we first divide it into subregions such that the area of a subregion is approximately 0.5–2.5 km^2, the topographic and environmental features within a subregion are similar, while different subregions have different topographic conditions and/or are separated by terrain obstacles (such as rivers and cliffs). For each subregion a_i, we estimate the location probability $p_t(i)$ based on the likelihood that the tourist travels from a_0 to a_i during the period $[0, t]$ using the following steps:

1) Predetermine a topographic suitability index $\beta_i \in [0, 1]$ of a_i. The easier access of the subregion to tourists, the larger the value of β_i.
2) Predetermine a weather suitability index $\gamma_{i,t} \in [0, 1]$ of a_i at time t (the subscript i will be omitted if the search region is not very large and all subregions share the same weather). We predefine a set of candidate $\gamma_{i,t}$ values for each combination of 44 weather conditions (sunny, cloudy, fog, slight haze, severe haze, etc.), 22 temperature ranges (below −19°C, 20 continuous intervals between [−19°C,40°C], and above 40°C), and 24 basic time clocks: the better the conditions, the larger the value of $\gamma_{i,t}$. Given a subregion a_i and time t, we query the $\gamma_{i,t}$ value based on the corresponding weather condition, temperature range, and the time clock at t.
3) Estimate the velocity $v_t(i)$ of the tourist when he/she traverses a_i at time t. This step can be further divided into the following sub-steps:
   3.1) Determine a benchmark velocity v of the tourist based on his/her basic information, e.g., $v = 5$ km/h for a healthy adult male and $v = 2.5$ km/h for a healthy elderly female.
   3.2) Determine a basic average velocity v_t of the tourist during $[t, t+1]$. At the beginning, $v_0 = v$, and v_t decreases with t as the tourist's physical strength diminishes. In this paper, we calculate

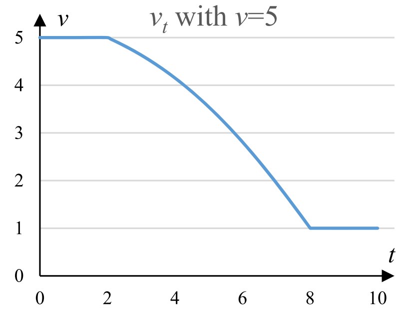


FIGURE 2. Illustration of the function for estimating the basic velocity, where the benchmark velocity $v = 5$ km/h.

v_t based on a logistic function as follows (where time t is in hours):

$$v_t = \begin{cases} v, & t<2 \\ 1+v-\dfrac{1+\exp(2.33)}{1+\exp(3.03-0.35t)}, & 2\le t\le 8 \\ 0.2v, & t>8 \end{cases} \tag{1}$$

Fig. 2 illustrates the function curve. It is easy to see that, the basic velocity decreases from v to $0.2v$ as the tourist's physical strength diminishes with time (decreases slowly between 3–5 hours and quickly between 5–8 hours). Note that in reality, after 8 hours, the tourist's velocity will continue to decrease to zero, and then he/she is very likely to rest for a long time, after which his/her velocity typically recovers to $0.3v$–$0.4v$, and then decreases again... However, to avoid too complex expressions, here we assume an average velocity of $0.2v$ after 8 hours.

3.3) Estimate the velocity $v_t(i)$ based on the basic velocity, topographic suitability index, and weather suitability index as follows:

$$v_t(i) = v_t\beta_i\gamma_{i,t} \tag{2}$$

Fig. 3 illustrates the change of $v_t(i)$ with β_i and $\gamma_{i,t}$. The principle of the equation is based on the fact that, according to exercise physiology [25], the physical performance of a person is significantly affected by environmental conditions, among which topographic and weather conditions are two main factors. Smaller β_i and $\gamma_{i,t}$ denote worse topographical and weather conditions, which can reduce the velocity $v_t(i)$. In our study, we carefully set the candidate values of β_i and $\gamma_{i,t}$ such that they have an approximately linear relation with the velocity.

4) Estimate an expected distance $d_t(i)$ traveled by the tourist from time 0 to t if he/she moves from a_0 towards a_i:

$$d_t(i) = \varepsilon\sum_{t'=1}^{t} v_{t'}(i_{t'}) \tag{3}$$

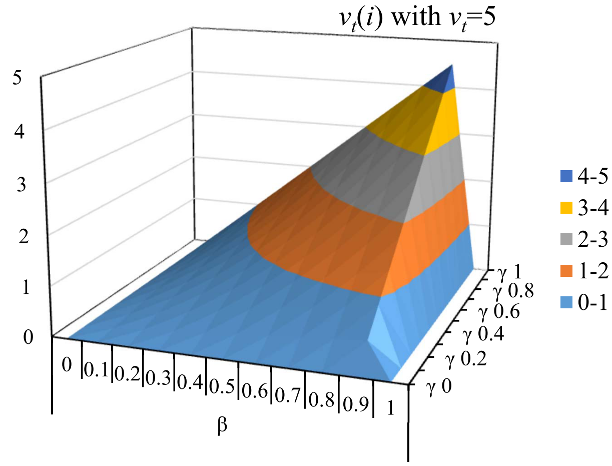


FIGURE 3. Illustration of the change of velocity $v_t(i)$ with suitability indices β_i and γ_t, where the basic velocity $v_t = 5$ km/h.

where $i_{t'}$ denotes the subregion in which the tourist is located at time t' under the assumption that the tourist travels from a_0 to a_i, and $\varepsilon \in [0, 1]$ is a parameter indicating the wilderness experience of the tourist: the smaller the value of ε, the less experienced the tourist and the more likely he/she will be disorientated and go around in circles, and thus the shorter the effective travel distance. If no information is available about the tourist's experience, we empirically set $\varepsilon = 0.75$.

5) Estimate the location probability $p_t(i)$ based on the difference $\Delta d_t(i) = d_t(i) - d_i$, the topographic suitability index β_i, and the weather suitability index γ_t. The basic principle is: the smaller the difference $|\Delta d_t(i)|$ and the fitter the geographical and weather conditions, the higher the location probability. In our study, after trying most typical regression methods, we find that the following combination of a power curve function and an exponential curve function fits the data well:

$$p_t(i) = \begin{cases} 0, & \Delta d_t(i) \le -\widehat{d} \\ c_1(\Delta d_t(i) + \widehat{d})^{10\beta_i\gamma_t}, & -\widehat{d} < \Delta d_t(i) \le 0 \\ c_1 c_2 b^{(1+\Delta d_t(i) - 20\beta_i\gamma_t)}, & \Delta d_t(i) > 0 \end{cases} \tag{4}$$

where $\widehat{d}$ is a predefined distance threshold typically calculated as t times the maximum speed of the tourist, b is a base in (0,1), and c_1 and c_2 are two coefficients that are adjusted to ensure that the function is continuous at $\Delta d_t(i) = 0$ and the sum of location probabilities equals 1. The changes of $p_t(i)$ with $\Delta d_t(i)$ are illustrated in Fig. 4 (where the distance is in km). That is, if $\Delta d_t(i) \le -\widehat{d}$, the probability is 0 because d_i is too long for the tourist to travel within time t; the probability increases with increasing $\Delta d_t(i)$ until $\Delta d_t(i) = 0$, where the probability is the highest as the time t is just sufficient for the tourist to arrive in a_i; the probability decreases with increasing $\Delta d_t(i) > 0$ as the tourist is more likely to move far away from a_i.

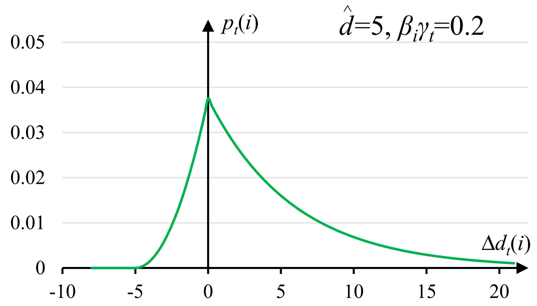


FIGURE 4. Illustration of the change of location probability $p_t(i)$ with $\Delta d_t(i)$ (in km).

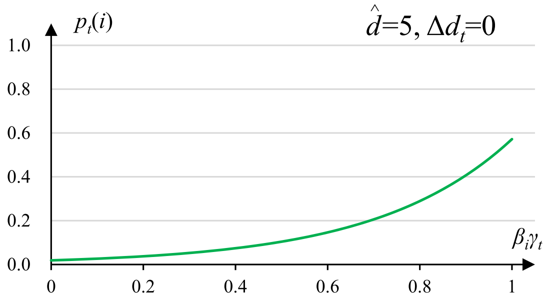


FIGURE 5. Illustration of the change of location probability $p_t(i)$ with $\beta_i\gamma_t$.

The probability also increases with increasing $\beta_i\gamma_t$, as illustrated in Fig. 5.

C. SEARCH MODES AND DETECTION PROBABILITY ESTIMATION

In general, a UAV can fly at any height between its minimum and maximum flight heights. However, in practice, we can define a fixed number K of UAV flight heights $\{h_1, h_2, \ldots, h_K\}$, and we say that the search mode is k when the flight height is h_k. Typically, h_1 is set to the lowest height at which the UAV can overlook the whole subregion (i.e., the UAV hovers once to complete the search), and h_k is set to the lowest height at which the UAV hovers more times than that at h_{k-1} to complete the search ($1 < k \leq K$), as illustrated by Fig. 6. Therefore, a larger k denotes a more detailed search mode, which requires a longer search time but has a higher probability of detecting the target.

For each search mode k ($1 \leq k \leq K$), under the assumption of the best visibility, we predetermine a basic detection probability $\rho(i, j, k)$ based on the topographic features of subregion a_i, the detection ability of the devices of UAV u_j, and the search height h_k. Then, we determine an index $\delta_{j,t} \in [0, 1]$ representing the impact of the weather condition at time t on the detection ability of the UAV, and calculate the posterior detection probability $\rho_t(i, j, k) = \delta_{j,t}\rho(i, j, k)$. For example, for a UAV using only cameras and optical sensors, $\delta_{j,t}$ takes one of the 11 values in $\{0, 0.1, 0.2, \ldots, 1\}$: the larger the value, the better the visibility.

D. DECISION VARIABLES AND OBJECTIVE FUNCTION

The problem is to determine the search path $\mathbf{x}_j$ of each UAV u_j, such that the tourist can be detected as early as possible. Here we represent $\mathbf{x}_j = \{(a_{j,1}, k_{j,1}), (a_{j,2}, k_{j,2}), \ldots, (a_{j,m_j}, k_{j,m_j})\}$, where $\{a_{j,1}, a_{j,2}, \ldots, a_{j,m_j}\}$ is the sequence of subregions to be searched by u_j, and $k_{j,i}$ is the search mode used for the i-th subregion $a_{j,i}$ ($1 \leq i \leq m_j$). Based on the search path $\mathbf{x}_j$, the search times $\Delta\tau(i, j, k)$, and the flight times $\Delta t(i, i', j)$, we can determine the action of UAV u_j at each time t. We use $x_t(j) = (i, k)$ to denote that u_j is searching in subregion a_i with mode k, and $x_t(j) = (i, i')^{\mathrm{T}}$ to denote that u_j is flying from a subregion a_i to another $a_{i'}$.

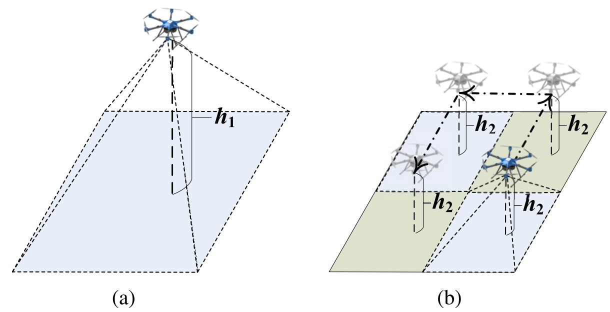


FIGURE 6. Illustration of two search modes at different heights. (a) The UAV hovers once at a height of h_1 to search the whole subregion. (b) The UAV hovers four times at a height of h_2 to search the whole subregion.

Let t^* be a hypothetical time at which the tourist is detected. Because the events of detection by different UAVs can be regarded as mutually exclusive, we can iteratively calculate the probability of $t^* = t$ for all t as follows:

$$P(t^* = 0) = 0 \tag{5}$$

$$\begin{aligned} P(t^* = t) &= P(t^* = t | t^* \geq t) P(t^* \geq t) \\ &= \Big[\sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{k=1}^{K} p_t(i)\rho_t(i, j, k|x_t(j))\Big] \\ &\quad \times \Big[1 - \sum_{t'=0}^{t-1} P(t^* = t')\Big], \quad t = 1, 2, \ldots, T \end{aligned} \tag{6}$$

where

$$\rho_t(i, j, k|x_t(j)) = \begin{cases} \rho_t(i, j, k), & \text{if } x_t(j) = (i, k) \\ 0, & \text{otherwise} \end{cases} \tag{7}$$

The objective function is to minimize the expected detection time:

$$\min E(t^*) = \sum_{t=1}^{T} t \cdot P(t^* = t) \tag{8}$$

According to Eqs. (5)–(8), the time complexity of the objective function is $O(mnKT^2/2)$.

E. EXTENSION FOR MULTIPLE TOURISTS

When there are a set R of independent tourists, we can use the method described in subsection III-B to estimate prior location probabilities $p_{r,t}(i)$ and posterior detection probabilities $\rho_{r,t}(i, j, k)$ for each tourist $r \in R$. As the tourists move independently, the events of detecting different tourists can be

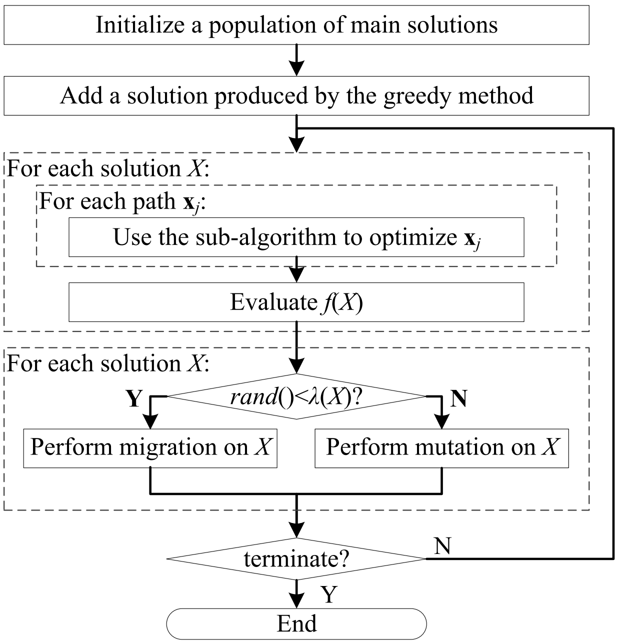


FIGURE 7. **The flowchart of the hybrid evolutionary algorithm for the UAV search planning problem.**

regarded as mutually exclusive, and thus we can iteratively calculate the probability of $t_r^* = t$ for $t = 0, 1, \ldots, T$, where t_r^* is a hypothetical time at which the tourist r is detected, based on Eqs. (5)–(7). The objective function of the extended problem can be expressed to minimize the sum of the expected detection times:

$$\min E = \sum_{r \in R} \sum_{t=1}^{T} t \cdot P(t_r^* = t) \tag{9}$$

or to minimize the weighted sum of the expected detection times:

$$\min E = \sum_{r \in R} \sum_{t=1}^{T} w_r t \cdot P(t_r^* = t) \tag{10}$$

where w_r is the importance weight of the tourist r.

Note that the decision variables of the extended problems are the same as those of the original problem, and thus the procedures of methods for the original problem are still applicable in such extensions.

IV. ALGORITHM

The above UAV search planning problem is highly complex, while the solution time can be very limited due to the requirement of fast response. To efficiently solve the problem, we propose a hybrid evolutionary algorithm consisting of a main algorithm for evolving a population of candidate solutions to the problem and a sub-algorithm for optimizing each UAV path in the solutions. Fig. 7 shows the flowchart of the problem-solving method, where $\lambda(X)$ denotes the migration rate of solution X (see Section IV-B), and *rand*() is a function for generating a number uniformly distributed in [0,1].

Algorithm 1 The Sub-Algorithm Based on the NEH and Tabu Search Heuristics

```
/* NEH heuristic */
```
1 Sort the subregions in C_j in decreasing order of the ratio of the target location probability to the distance from u_j;
2 Construct a partial schedule $\mathbf{x}_j$ of the first two subregions in C_j to maximize the current fitness;
3 Let $i = 3$;
4 **while** $i < |C_j|$ **do**
5   Insert the i-th subregion to $\mathbf{x}_j$ at the position, among the i possible ones, which maximizes the current fitness;
6     $i \leftarrow i + 1$;

```
/* tabu search */
```
7 Initialize an empty tabu list T_L;
8 Let $s = 0$, $\mathbf{x}_j^* = \mathbf{x}_j$;
9 **while** $s < \hat{s}$ **do**
10   Let $i^* = \underset{1 \le i \le |C_j|-1, i \notin T_L}{arg\,max} f(\mathbf{x}_j^{(i)})$, where $\mathbf{x}_j^{(i)}$ is the neighbor obtained by swapping the i-th and $(i+1)$-th subregions of $\mathbf{x}_j$;
11     $\mathbf{x}_j \leftarrow \mathbf{x}_j^{(i^*)}$;
12   Add i^* to T_L;
13   **if** $|T_L| > \hat{L}$ **then** remove the first element from T_L;
14   **if** $f(\mathbf{x}_j) < f(\mathbf{x}_j^*)$ **then** $\mathbf{x}_j^* \leftarrow \mathbf{x}_j$;
15     $s \leftarrow s + 1$;
16 **return** $\mathbf{x}_j^*$;

A. THE SUB-ALGORITHM FOR PATH OPTIMIZATION

Suppose a set $C_j \subset A$ of subregions have been assigned to UAV u_j, the sub-algorithm produces the search path $\mathbf{x}_j$ of u_j based on the NEH heuristic [26] and tabu search method [27], [28]. The fitness of a path $\mathbf{x}_j$ is evaluated as the ratio of the total detection probability to the total time consumed along the path:

$$f(\mathbf{x}_j) = \frac{\sum_{i=1}^{|\mathbf{x}_j|} p_{t_{j,i}}(a_{j,i}) \rho_{t_{j,i}}(a_{j,i}, j, k_{j,i})}{\sum_{i=1}^{|\mathbf{x}_j|} \Delta\tau(a_{j,i}, j, k_{j,i}) + \sum_{i=1}^{|\mathbf{x}_j|-1} \Delta t(a_{j,i}, a_{j,i+1}, j)} \tag{11}$$

where $t_{j,i}$ is the time at which u_j begins to search in the i-th subregion in its path given by:

$$t_{j,1} = \Delta t(a_{j,0}, a_{j,1}, j) \tag{12}$$

$$t_{j,i} = t_{j,i-1} + \Delta\tau(a_{j,i-1}, j, k_{j,i-1}) + \Delta t(a_{j,i-1}, a_{j,i}, j), \quad \forall 1 < i \le |\mathbf{x}_j| \tag{13}$$

The NEH heuristic is extended for UAV search path construction as shown in Lines 1–6 of Algorithm 1, where the search mode of u_j in each subregion a_i is set to a k, among the K candidate modes, which maximizes the ratio of detection probability $p_t(i)\rho_t(i, j, k)$ to the search time $\Delta\tau(i, j, k)$.

The initial path is then iteratively improved by a tabu search procedure shown in Lines 7–16 of Algorithm 1. It iteratively moves the current solution to the best neighboring solution that is not forbidden by the tabu list, where the neighborhood structure is defined by swapping two adjacent subregions in the search path. In addition, on each neighbor we also perform a local search by changing the search modes k in the swapped subregions to $k \pm 1$. Empirically, the maximum number $\widehat{s}$ of tabu search steps is set to $|C_j|/2$, and the tabu length $\widehat{L}$ is set to 6. Thus, the sub-algorithm visits at most $m/2$ neighboring solutions (but in most cases the average $|C_j|/2$ is much less than $m/2$), and its worst time complexity is $O(m^2nKT^2/4)$.

B. THE MAIN EVOLUTIONARY ALGORITHM

The main algorithm initializes a population of N solutions, including $N-1$ randomly generated solutions and a solution generated by a greedy procedure which always chooses the next step with the largest payoff (in terms of the ratio of the detection probability to the time consumed), as shown in Algorithm 2. Such a potentially good solution can accelerate the convergence speed of the algorithm. The time complexity of the greedy procedure is $O(Kmn^2 \min(T, m)/2)$, which is less than the complexity of the objective function if $n<m<T$.

Algorithm 2 The Greedy Procedure to Produce a Potentially Good Solution to the Problem

Let $t = 0, A' = A$;
while $t < T \wedge |A'| > 0$ **do**
  Let U' be the set of idle UAVs;
  while $|U'| > 0 \wedge |A'| > 0$ **do**
    Let $i^* = 0, j^* = 0, k^* = 0, pay = 0$;
    foreach $u_j \in U'$ **do**
      Let a_i be the subregion in which u_j is located;
      foreach $a_{i'} \in A'$ **do**
        Let $t' = t + \Delta t(i, i', j)$;
        for $k = 1$ *to* K **do**
          Let $pay' = \frac{p_{t'}(i')\rho_{t'}(i',j,k)}{\Delta t(i,i',j)+\Delta\tau(i',j,k)}$;
          if $pay' > pay$ **then**
            $(i^*, j^*, k^*, pay) \leftarrow (i', j, k, pay')$;
    Add (i^*, k^*) to the search path $\mathbf{x}_{j^*}$, remove u_{j^*} from U', and remove a_{i^*} from A';
  $t \leftarrow t + 1$, update the status of the UAVs;
return $X = \{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_n\}$;

The main algorithm evolves the solutions using two operators: migration and mutation. The migration operator, taking from the BBO metaheuristic [29], makes a solution migrate features from other solutions. For each solution X in the population, we use a nonlinear model from [30] to calculate a migration rate $\lambda(X)$ as:

$$\lambda(X) = 0.5 - 0.5 \cos\left(\frac{f(X) - f_{\min} + \epsilon}{f_{\max} - f_{\min} + \epsilon}\pi\right) \tag{14}$$

where $f_{\max}$ and $f_{\min}$ are the maximum and minimum objective function values among the population, respectively, and ϵ is a very small number to avoid division-by-zero.

At each generation, each solution X has a probability $\lambda(X)$ of immigrating features from other solutions, which are selected from the best half of the population with probabilities proportional to their fitness, or inversely proportional to their migration rates. Algorithm 3 presents the migration procedure, where $C(\mathbf{x}_j)$ denotes the set of subregions in the path $\mathbf{x}_j$. The time complexity of the migration procedure is $O(m^2n^2KT^2/4)$.

Algorithm 3 The Migration Procedure

for $j = 1$ *to* n **do**
  Select an emigrating solution X' from the best half of population with a probability proportional to $1-\lambda(X')$;
  Let $A_j = C(\mathbf{x}_j)\backslash C(\mathbf{x}'_j)$;
  Randomly remove a subset of subregions in A_j from $\mathbf{x}_j$;
  Let $A'_j = C(\mathbf{x}'_j)\backslash C(\mathbf{x}_j)$;
  Randomly add a subset of subregions in A'_j to $\mathbf{x}_j$;
  Call Algorithm 1 to reorder $\mathbf{x}_j$;

After migration, some subregions may be repeatedly searched. Suppose that a subregion a_i is in the paths of multiple UAVs, the set of which is denoted by $U(a_i)$. We improve the solution by only retaining a UAV u_{j^*}, among all the UAVs in $U(a_i)$, whose ratio of the detection probability to the time consumed in a_i is the maximum:

$$j^* = \underset{u_j \in U(a_i)}{arg\,max} \frac{\rho_t(i, j, k)}{\Delta t_{pre(i),i,j} + \Delta\tau_{i,j,k} + \Delta t_{i,next(i),j}} \tag{15}$$

where $pre(i)$ and $next(i)$ respectively denote the subregions previous and next to a_i in the path of u_j. Then, a_i is removed from the path of other UAVs in $U(a_i)$. Afterwards, we try to add unexplored subareas (if any exist) to the paths of those UAVs, also in decreasing order of the ratio of the detection probability to the time consumed, until the operational time exceeds T.

If a solution X is not selected for migration, it will be mutated by regenerating the search paths for a part of UAVs. Similar to the propagation operator of the water wave optimization (WWO) metaheuristic [31], each solution X is assigned with a mutation rate $\mu(X)$, which is uniformly initialized to 0.5 and then updated at each generation as:

$$\mu(X) = \mu(X) \cdot \alpha^{-(f_{\max} - f(X) + \epsilon)/(f_{\max} - f_{\min} + \epsilon)} \tag{16}$$

where α is a mutation reduction coefficient typically set to 1.0026. According to Eq. (16), a fitter solution has a smaller mutation rate and hence explores a narrow area around it, while a worse solution has a larger mutation rate and hence explores a wide area. Moreover, the average mutation rate decreases with the number of generations, which can also accelerate the convergence. Algorithm 4 presents the mutation procedure. The mutated solution, if better than the original solution X, will replace X in the population. The time complexity of the mutation procedure is also $O(m^2n^2KT^2/4)$.

Algorithm 4 The Mutation Procedure

```
1 Let A' = A, U' = ∅;
2 for j = 1 to n do
3 |  if rand() < μ(X) then U' ← U' ∪ {u_j} ;
4 |  else remove the subregions in x_j from A' ;
5 Randomly assign the subregions in A' to UAVs in U';
6 foreach u_j ∈ U' do
7 |  Call Algorithm 1 to reorder x_j;
```

If a solution has not been improved for $\widehat{g}$ (a control parameter typically set to 6) generations, it will be replaced with a new solution randomly generated so as to improve solution diversity.

Let G be the maximum number of the generations of the hybrid evolutionary algorithm. At each generation, for each of the N solutions in the population, the sub-algorithm is called n times, and either the migration or the mutation procedure is called once, and thus the total time complexity of the algorithm is $O(GNm^2n^2KT^2/2)$.

V. RESULTS

To test the performance of the proposed method, we construct a variety of test instances in three regions, including the Jiuzhaigou National Nature Reserve, Hua'eshan National Nature Reserve, and Taibai Mountain National Forest Park, the search areas of which are approximately 64,000, 48,000, and 8,000 ha, respectively. On each region, we simulate 100 incidents of missing tourists, and randomly generate their routes based on the location probability distribution in the subregions. Besides, we add five real-world incidents of missing tourists, including two incidents in Jiuzhaigou, two in Hua'eshan, and one in Taibai Mountain. For each incident, we respectively simulate the use of two, four, and eight UAVs to search for the tourist. The UAV functions conform to the specification of the DJI Inspire 2 with a Zenmuse X5R camera (i.e., we use identical UAVs in the test). The experimental environment is a workstation with an i7-6500 2.5GH CPU, 8GB DDR4 RAM, and an NVIDIA Quadro M500M card.

For comparison, we implement eight other methods to solve the instances. The methods can be divided into two groups. The first group consists of the following four popular UAV search planning methods, which are used to compare with the UAV search planning framework proposed in this paper:

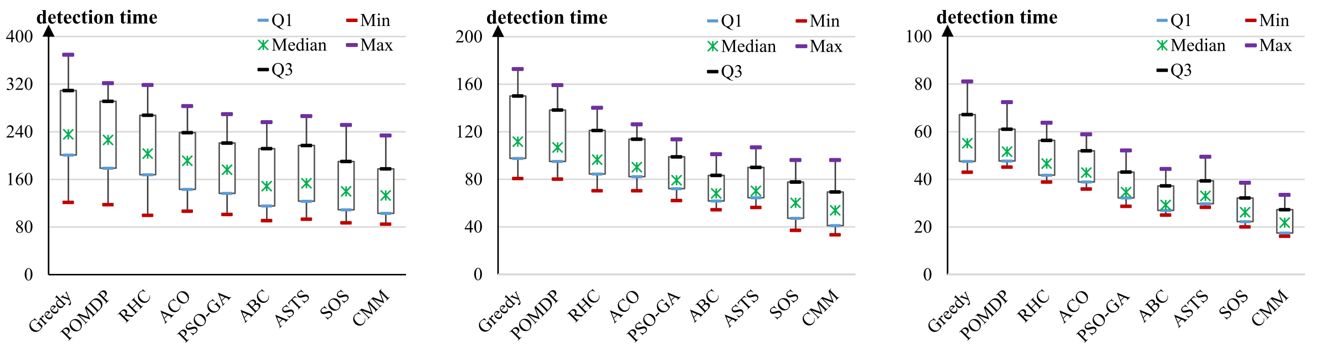
- A greedy (one-step lookahead) method [2] that always chooses an unexplored subarea with the maximum location probability and assign it to the closest idle UAV.
- A partially observable Markov decision process (POMDP) based heuristic that yields the action of each UAV to maximize the expected reward (detection probability) over the time horizon [3].
- A method based on Gaussian mixture model and receding horizon control (RHC) where subregions are prioritized hierarchically based on their Gaussian components and then allocated to UAVs to maximize the predicted reward [32].
- An ACO algorithm that combines the learning capabilities of the ant colony with the minimum-time-search heuristic [21].

The second group consists of the following four state-of-the-art metaheuristics adapted to our problem for comparison with the proposed evolutionary algorithm using path migration and mutation:

- A two-phased evolutionary algorithm that integrates PSO and GA [33], denoted by PSO-GA.
- An artificial bee colony (ABC) algorithm for cooperative task assignment and scheduling [34].
- A hybrid max-min ant system combined with tabu search (ASTS) [35].
- A symbiotic organism search (SOS) optimization algorithm [36].

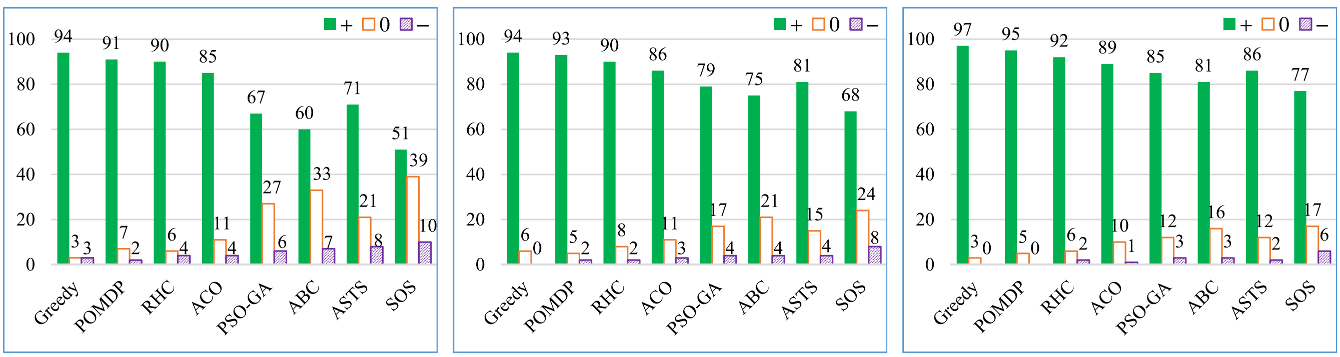
For fairness, we set the maximum allowable CPU time to 900 seconds for all the methods, because in practice it typically requires 10-15 minutes to prepare and mobilize UAVs since the report of a missing event, and such a time period is just sufficient for producing a solution in response to the event. The control parameters of the algorithms are all fine-tuned on the test instances. For the proposed algorithm combining migration, mutation, and local search (denoted by CMM), we set the tabu length to 12, and set the population size to 60 on the instances of the Jiuzhaigou and Hua'eshan regions and 45 of the instances in the Taibai Mountain, respectively. Because the last five methods and our method are inherently stochastic optimization algorithms, we run each of them 30 times on each instance, and record the median detection time over the 30 runs.

Fig. 8 presents the box plots of the expected detection times obtained by our method and the other eight methods on the 100 simulated incidents in the Jiuzhaigou region. Furthermore, we conduct a nonparametric Wilcoxon rank sum test to compare the results of our method with those of the other methods on each instance, and present the test results in Fig. 9, where 0 indicates that there is no significant difference between the two methods (at a 95% confidence level), + indicates that the result of our method is significantly better than that of the corresponding comparative method, and − vice versa. From the results, it can be observed that the greedy method using the local one-step lookahead search policy exhibits the worst performance, because maximizing the payoff of the next step often results in a low payoff over the whole time horizon. The POMDP method extends the local search steps and thus obtains better results than Greedy does, but the improvement is slight. By using a hierarchical strategy to control the local search, the RHC method achieves further performance improvement over the Greedy and POMDP methods. The ACO method that uses



(a) (b) (c)

FIGURE 8. The maximum, minimum, median, first quartile (Q1), and third quartile (Q3) of the expected detection times (in minutes) obtained by the comparative methods on the 100 simulated incidents in the Jiuzhaigou region. (a) Using two UAVs. (b) Using four UAVs. (c) Using eight UAVs.



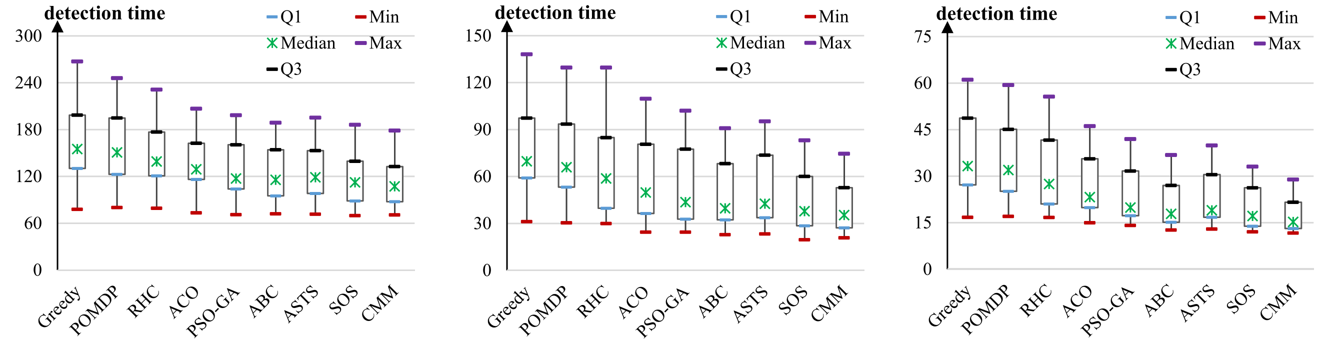
(a) (b) (c)

FIGURE 9. Statistical significance tests on the result of our method compared with those of the other methods on the 100 simulated incidents in the Jiuzhaigou region. 0 indicates that there is no significant difference between two methods (at a 95% confidence level), + indicates that the result of our method is significantly better than that of the corresponding comparative method, and – vice versa. (a) Using two UAVs. (b) Using four UAVs. (c) Using eight UAVs.

the global minimum time search policy achieves a significant performance improvement over the first three local search methods, demonstrating that planning UAV paths from the global perspective is crucial for solving the problem of UAV search for missing tourists.

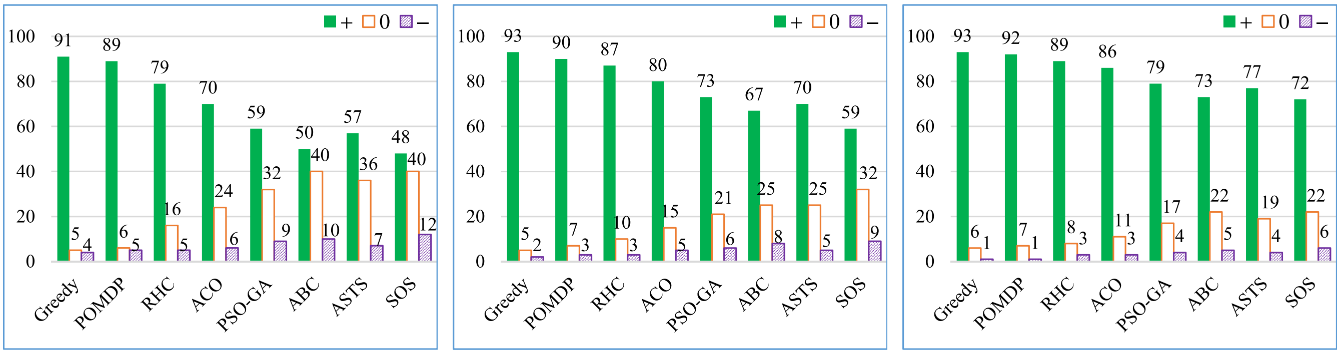
The expected detection times obtained by the last five methods are significantly shorter than those of the first four methods, validating the effectiveness and efficiency of the proposed search planning framework for the problem. Among the last five metaheuristics using the search planning framework proposed in this paper, the hybrid PSO-GA yields the longest median expected detection time, because both the PSO learning operator and the GA crossover operator easily lead to premature convergence. SOS yields better results than PSO-GA, ABC, and ASTS do, but its performance is still worse than our CMM algorithm on most of the instances. Among all the comparative methods, CMM obtains the shortest median expected detection time, because its path migration and mutation operators can well balance the global exploration and local exploitation, and its sub-algorithm can effectively improve the solution accuracies. Consequently, the proposed algorithm exhibits a promising performance in solving this complex problem.

From Fig. 9(a)–(c), we can also observe that, on instances using more UAVs, the performance advantages of our method are more significant. In terms of statistical tests, our CMM method achieves significantly better results than the other methods on a majority of instances. Compared to the first four UAV search methods, our method achieves significantly better results on approximately 90% of the instances. Compared to the last four metaheuristics, when two UAVs are used, our CMM algorithm achieves significantly better results than PSO-GA, ABC, ASTS, and SOS on 67, 60, 71, and 51 among the 100 instances, respectively. When eight UAVs are used, CMM obtains significantly better results than the other four metaheuristics on 85, 81, 86, and 77 instances, respectively. On the contrary, none of the other methods can obtain significantly better results than our method on more than ten instances. As the solution space increases exponentially with the number of UAVs, the test results demonstrate that the combination of the path migration and mutation operators of our algorithm can explore the large solution space of the



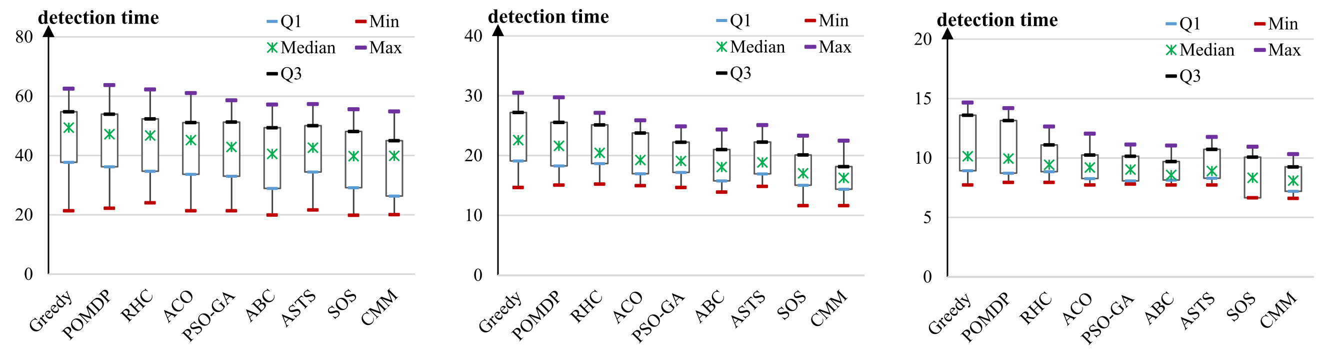
(a) (b) (c)

FIGURE 10. **The maximum, minimum, median, first quartile (Q1), and third quartile (Q3) of the expected detection times (in minutes) obtained by the comparative methods on the 100 simulated incidents in the Hua'eshan region. (a) Using two UAVs. (b) Using four UAVs. (c) Using eight UAVs.**



(a) (b) (c)

FIGURE 11. **Statistical significance tests on the result of our method compared with those of the other methods on the 100 simulated incidents in the Hua'eshan region. 0 indicates that there is no significant difference between two methods (at a 95% confidence level), + indicates that the result of our method is significantly better than that of the corresponding comparative method, and – vice versa. (a) Using two UAVs. (b) Using four UAVs. (c) Using eight UAVs.**



(a) (b) (c)

FIGURE 12. **The maximum, minimum, median, first quartile (Q1), and third quartile (Q3) of the expected detection times (in minutes) obtained by the comparative methods on the 100 simulated incidents in the Taibai Mountain. (a) Using two UAVs. (b) Using four UAVs. (c) Using eight UAVs.**

problem much more efficiently than the evolutionary operators of the other metaheuristics.

Fig. 10 and Fig. 12 present the box plots of the expected detection times obtained by the comparative methods on the simulated incidents in the Hua'eshan region and the Taibai Mountain, respectively, and Fig. 11 and Fig. 13 present the corresponding statistical test results. As we can observe, the results are similar to those in the Jiuzhaigou region, that is, the five metaheuristics using our UAV search framework exhibit significantly better performance than the other four UAV search methods, and the proposed CMM algorithm obtains the best results among all the methods. Comparatively, the performance advantages of the proposed method are more significant on the instances of the Jiuzhaigou and

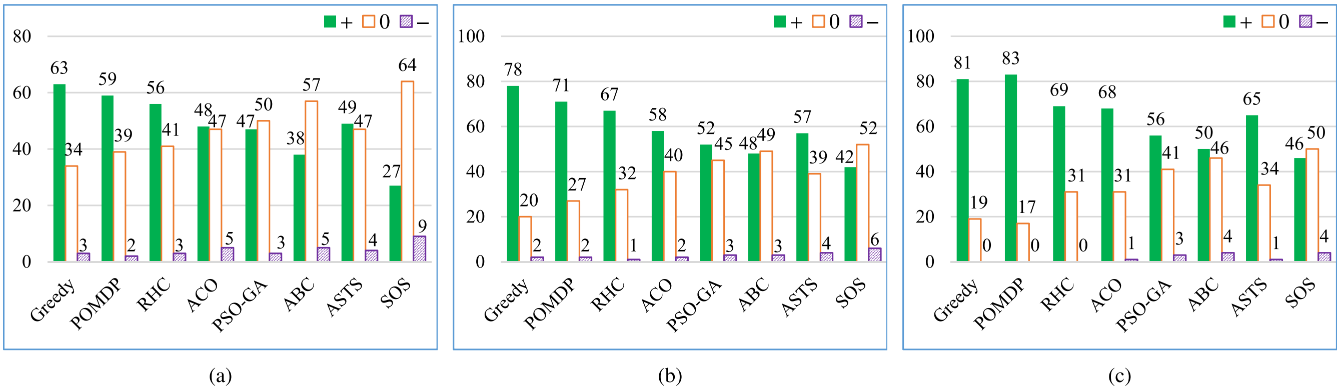


FIGURE 13. Statistical significance tests on the result of our method compared with those of the other methods on the 100 simulated incidents in the Taibai Mountain. 0 indicates that there is no significant difference between two methods (at a 95% confidence level), + indicates that the result of our method is significantly better than that of the corresponding comparative method, and – vice versa. (a) Using two UAVs. (b) Using four UAVs. (c) Using eight UAVs.

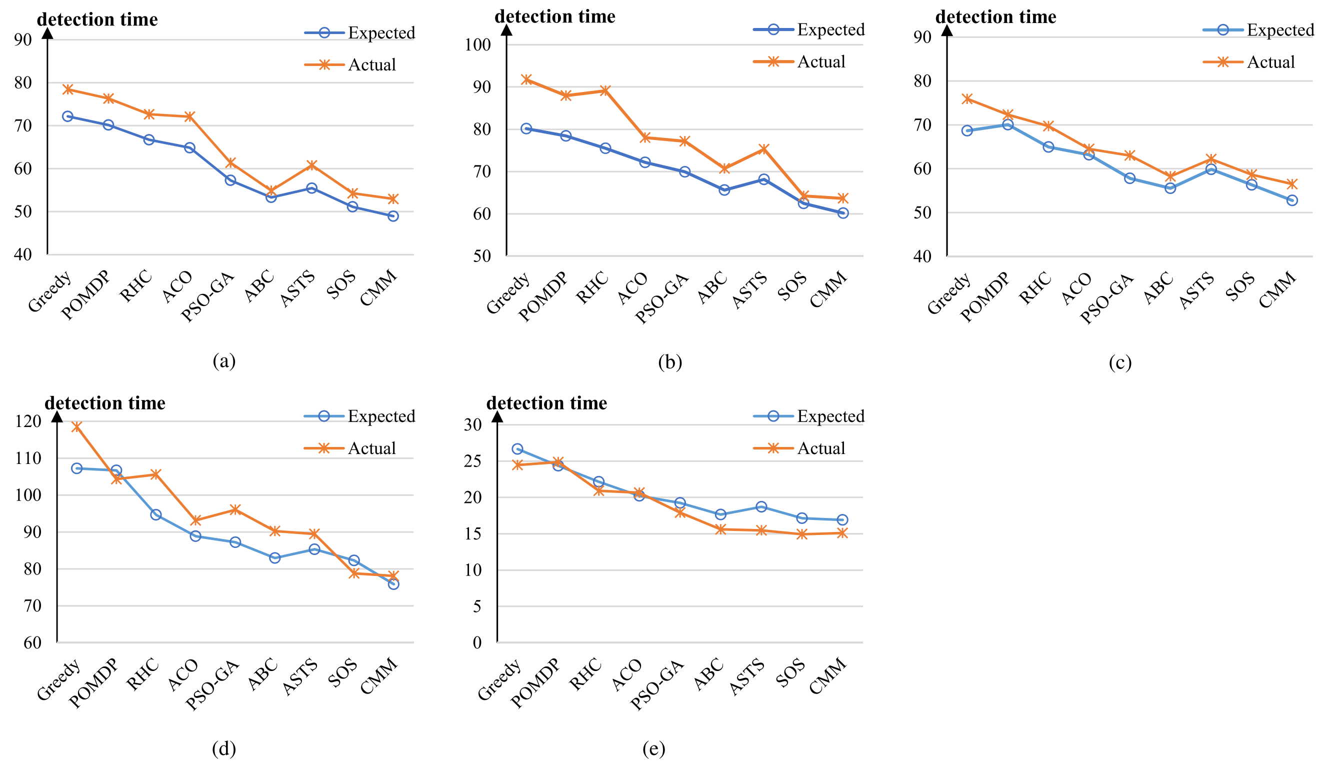


FIGURE 14. Expected and actual detection times (in minutes) obtained by the nine UAV search methods in the five real-world incidents of tourist missing. (a) Incident 1 (four UAVs in Jiuzhaigou). (b) Incident 2 (three UAVs in Jiuzhaigou). (c) Incident 3 (three UAVs in Hua'eshan). (d) Incident 4 (two UAVs in Hua'eshan). (e) Incident 5 (two UAVs in Taibai Moutain).

Hua'eshan regions than those on the instances of the Taibai Mountain, because the area (and consequently the number of subregions) of the Taibai Mountain are much smaller. This also demonstrates that the proposed method is well designed for solving large-size instances of this complex problem.

For the five real-world incidents, the numbers of UAVs available in local emergency departments at those times were four, three, three, two, and two, respectively, which are also used in our tests. For each instance, we also employ each of the above nine methods to produce a UAV search solution. Besides the expected detection time (i.e., the objective function value) of the solution, we calculate an "actual" detection time, i.e., the earliest time at which the missing tourist enters into the detection range of (at least) a UAV, according to the UAV paths in the solution and the real route of the tourist. Fig. 14 presents the results on the five real-world problem instances. The results show that the difference between the expected and actual detection times of the methods are relatively small (typically within 10%), demonstrating the practicability and rationality of the proposed problem model as well as the probability estimation method. Typically, the expected detection times of the methods are longer than their actual detection times on the first four instances, but the opposite is the case on the last instance. This is because the areas of search regions of the first four instances are large, and thus the estimation of tourist location probability is more likely to deviate from the actual route. On the five real-world instances, our CMM algorithm still exhibits the best performance (in terms of either expected or actual detection time) among the nine methods. As far as we know, the local emergency departments have mainly used greedy methods similar to the method in [2] for UAV search planning. The main advantage of the greedy methods is that they can produce a solution within only 1–3 minutes, while our algorithm uses 5–10 minutes for middle-size instances and approximately 15 minutes for large-size instances. However, in practice, the algorithm can be executed in parallel with the preparation of UAVs. More importantly, compared to the greedy method, using our method shortens the actual detection times by more than 20 minutes on the first four instances and approximately 10 minutes on the last instance. Consequently, our method has a promising performance in response to the life-critical tasks.

VI. CONCLUSION

In this paper we present a problem of multiple UAV search for missing tourists, the objective of which is to minimize the expected detection time calculated based on the location probability distribution. We propose a hybrid evolutionary optimization method consisting of a main algorithm for evolving a population of main solutions and a sub-algorithm for optimizing each UAV search path. Computational results demonstrate that the proposed method exhibits promising performance on a wide variety of test instances and can provide a significant improvement in real-world operations.

The presented problem can be extended for a variety of target search problems with time-varying distribution of target location probabilities, such as searching for survivors in disasters, searching for dubious targets in battlefields, searching for escaping criminals, etc. In particular, the proposed probability estimation method provides a good basis for estimating the probabilities of target location in different scenarios. Our hybrid evolutionary optimization method can also be easily adapted or extended for this class of problems.

Currently, we are popularizing the proposed method to more nature reserves and scenic areas in China and neighboring countries. Subdividing the search regions and predetermining the parameters for probability estimation and instance construction are heavy tasks, but can help in improving our method. A new requirement from the local emergency department is to optimally deploy the available UAVs in the search regions to facilitate future search operations [37], which can be integrated into our UAV search problem. We are also extending our problem and solution method to UAV search for a large number of victims in large-scale rescue operations (such as in natural disasters), where we must pay more attention to the probability distribution of a population rather than an individual.

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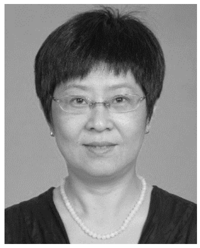

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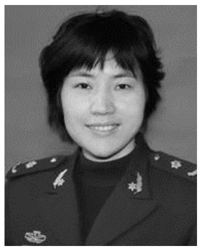

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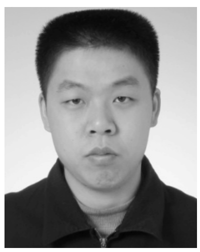

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