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Collaborative Human–UAV Search and Rescue for Missing Tourists in Nature Reserves

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Abstract. The use of unmanned aerial vehicles (UAVs) is becoming commonplace in search-and-rescue tasks in complex terrains. In the literature, there are a number of studies on UAV search with the objective of minimizing search time and/or maximizing detection probability. However, little effort has been devoted to collaborative human and UAV search, which is necessary in many applications in which humans must ultimately reach the target. In this paper, we present a collaborative human–UAV search-planning problem, the objective of which is to minimize the expected time for human rescuers to reach the target. For this highly complex problem, traditional exact algorithms would be very time-consuming or even impractical for solving even relatively small instances. We propose an evolutionary algorithm that uses biogeography-inspired operators to efficiently evolve a population of candidate solutions to the optimal or near-optimal solution within an acceptable time. Computational experiments demonstrate the advantages of our algorithm over many popular algorithms. The proposed method has been successfully applied to two real-world search-and-rescue operations to find missing tourists in a nature reserve in China. Compared with the old method used by the rescue department, our method shortened the time required for reaching the targets by approximately 79 and 147 minutes in the two cases, respectively, providing a great improvement in the life-critical operations.

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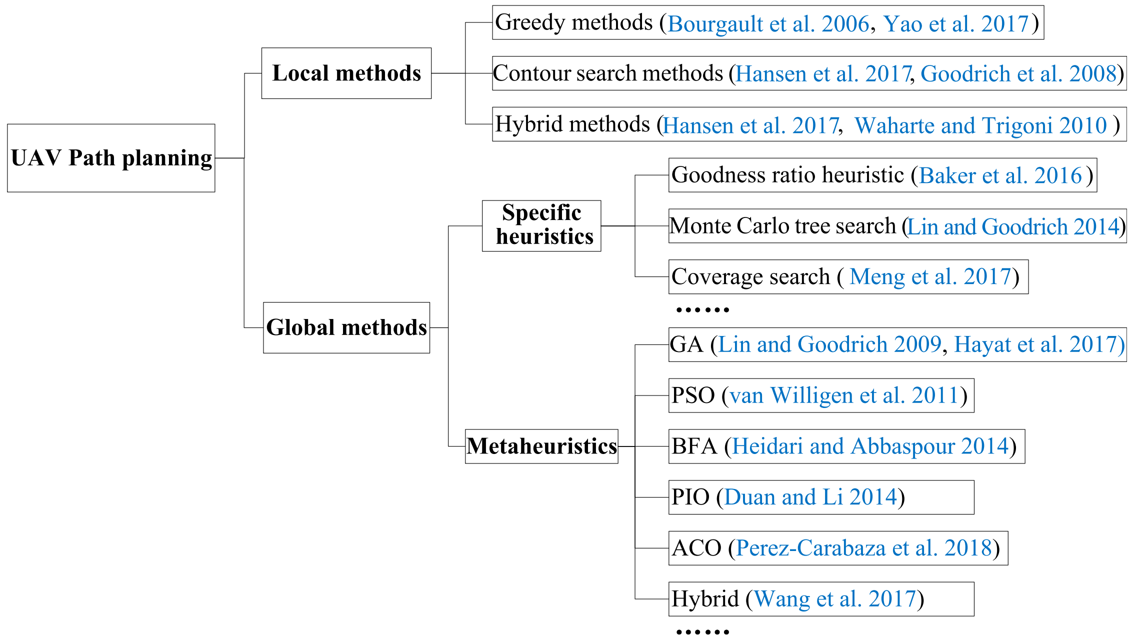
Keywords: unmanned aerial vehicle (UAV) • search and rescue • collaborative search • bioinspired algorithm

Introduction

Many tourists go missing throughout the world each year. To find them, great efforts are made in search-and-rescue operations. Such operations can benefit from the use of unmanned aerial vehicles (UAVs), which provide sensory data, such as images and videos, to find evidence about target locations, especially in complex terrains (Murphy et al. 2008, Waharte and Trigoni 2010, Tan and Zheng 2013). With the rapid improvement of the functionality, flexibility, and autonomy of UAVs, their use in search and rescue is becoming commonplace. For example, in January 2017, Australian water police used an Eagle-3 UAV to locate two missing tourists in Ku-ring-gai Chase National Park within one hour (Morcombe 2016). On February 5, 2019, a DJI drone detected a student missing from the California School for the Deaf shortly after it took off and then guided the police to the student, who was cold and hungry (Jun 2019). UAVs were also used in humanitarian operations, including the 2015 Tianjin Port explosion, the 2016 Kaohsiung earthquake, and the Syrian conflict.

There have been numerous studies on UAV path planning for target search. The methods can be categorized into local and global search methods depending on whether path planning is considered as a global optimization problem. Local search methods include greedy methods (i.e., methods that always choose a direction with maximum detection probability or the largest payoff; Bourgault et al. 2006, Yao et al. 2019), 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; Hansen et al. 2007, Goodrich et al. 2008), and variants and combinations of these (Hansen et al. 2007, Waharte and Trigoni 2010). Global search methods can be further divided into problem-specific heuristic methods and metaheuristic methods (Zheng et al. 2015). The former include the goodness ratio heuristic (Lin and Goodrich 2014), the Monte Carlo tree search (Baker et al. 2016), and the improved coverage search with geometric relations (Meng et al. 2017). The latter include genetic algorithms and their variants (Lin and Goodrich 2009, Hayat et al. 2017)

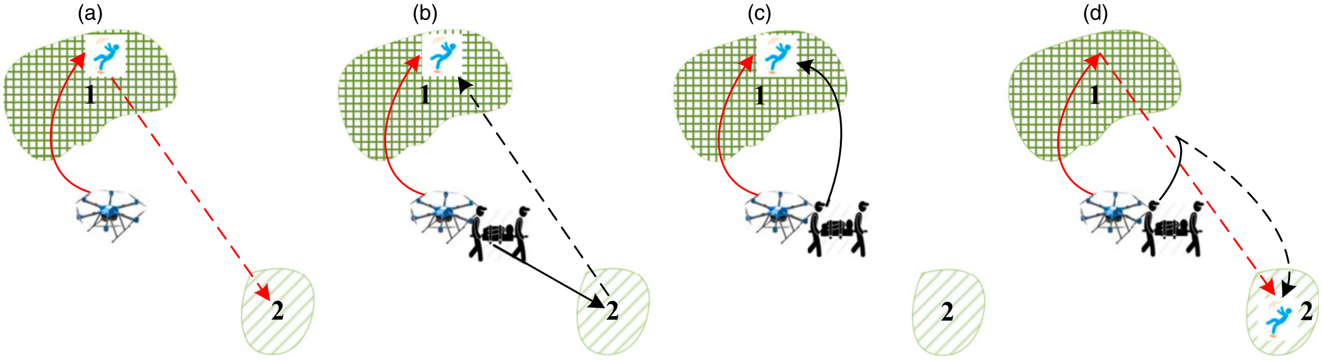
Figure 1. (Color online) Classification of UAV Path-Planning Methods for Search and Rescue in the Literature, Including Relevant Citations



and other nature-inspired methods, such as particle swarm optimization (van Willigen et al. 2011), thbacterial foraging algorithm (Heidari and Abbaspour 2014), pigeon-inspired optimization (PIO) (Duan and Li 2014), and ant colony optimization (ACO) (Perez-Carabaza et al. 2018), as well as combinations of these (Wang et al. 2017). Figure 1 presents a classification chart of existing UAV search-planning methods.

The objectives of almost all UAV search-planning problems studied in the literature are to minimize search time and/or maximize detection probability. However, in many search-and-rescue operations, detecting the target is an important milestone but not the ultimate goal. For example, a tourist lost in the wild for several days is often in poor condition and needs to be reached by medical professionals as early as possible. Using a human rescue team and a UAV to search simultaneously in two opposite directions would be likely to reduce detection time but could greatly prolong the reaching time if the search direction of the human team is wrong. Figure 2 illustrates such a case with one human team and one UAV. The case can be much more difficult when there are multiple teams and UAVs. Unfortunately, little effort has been devoted to collaborative human and UAV search, which is necessary in many applications in which the target must be ultimately reached by human rescuers. The studies of Bertuccelli and Cummings (2011) and

Figure 2. (Color online) A Simple Case of Search and Rescue by UAV and Human Teams in Two Regions, in Which Region 1 Has a Higher Target-Location Probability



Notes. In panel (a), only a UAV is used. To minimize the expected search time, the UAV first searches region 1. In panel (b), a UAV and a human team are used. To minimize the expected search time, the UAV searches region 1, and the team searches region 2. When the target is in region 1, the team will reach it too late. In panel (c), a UAV and a team are used. To minimize the expected time to reach the target, the UAV and the team cooperate in the search. When the target is in region 1, the team will reach it quickly. In panel (d), the UAV and the team cooperate in the search as they do in case (c). When the target is in region 2, the team will reach it on time because the UAV is much faster than the human team.

Liu (2016) consider human–UAV cooperation, but they also focus on target detection while emphasizing the dominant role of humans in controlling the search.

In this paper, we present a collaborative human–UAV search-planning problem, the objective of which is to minimize the expected time for human rescuers to reach the target. To solve this complex combinatorial optimization problem, we propose an evolutionary algorithm that evolves a population of candidate solutions toward the global optimal (or a near-optimal) solution by bioinspired operations. Computational experiments show the advantage of our algorithm over many popular algorithms. The proposed problem and algorithm have been successfully applied to real-world search-and-rescue operations for finding missing tourists in Hua'eshan National Nature Reserve in China. Our approach can also be used or extended for target searching in a variety of field environments.

Problem Description

Consider that we are using a set of human rescue teams and a set of UAVs to search simultaneously for a target (e.g., one or a team of missing tourists) in a wide area (e.g., a nature reserve). The search area is divided into a number of subareas. The target location is unknown, but we have a prior probability of target location in each subarea, which is estimated based on the target information (e.g., the time and place last seen) and environmental features (e.g., rivers and roads). The human teams and UAVs can use different modes to search each subarea: the more detailed the search mode, the higher is the probability that the target will be detected if the target is actually in the subarea. The problem is to determine the search sequence (of subareas) for each human team and each UAV and determine the search mode of each team and each UAV in each subarea such that the expected detection time is minimized. The mathematical formulation of the problem is given in the "Problem Formulation" section of the appendix.

Following are some guidelines for constructing problem instances:

• *Area subdivision:* The search area is divided mainly based on topographic conditions (i.e., the topographic and environmental features within a subarea are similar, and different subareas have different topographic conditions and/or are separated by terrain obstacles). Usually, a subarea covers an area of 0.5–2 km^2: an excessively large subarea cannot be effectively searched by a UAV, and excessively small subareas can result in a large number of subareas and therefore increase the difficulty of the problem.

• *Prior probability estimation:* Typically, the prior target location probability of each subarea is estimated based on the environmental features of the subarea and the distance from the target's last known location to the subarea. Two factors contribute to a higher probability of finding the target: (1) an environment that is more suitable for travel and (2) being closer to the target's last known location. An example of the estimation of the location probability distribution is given in the "Estimating the Prior Distribution on Target Location" section of the appendix.

• *Detection probability estimation:* The more experienced the team or the more advanced the detection devices of the UAV, the higher is the detection probability.

In general, to use our approach, the potential search area should be investigated in advance such that the area subdivision and most parameters for probability estimation have been predetermined. Otherwise, the instance construction can be time-consuming and thus cannot meet the emergency needs. Moreover, we should get the information (e.g., physical conditions and behavior intentions) of the missing persons in as much detail as possible. When searching for a person in an uninvestigated area and with little available information, using local greedy search or contour search methods is preferable.

Solution Method

The problem we present is highly complex; thus, traditional exact algorithms would be very time-consuming or impractical for even relatively small instances. We propose a bioinspired algorithm to solve the problem using the following steps:

1. Randomly initialize a population of candidate solutions.
2. Add a solution produced by a greedy procedure to the population.
3. For each solution, use Equations (A.12) and (A.13) in the section "A Bio-Inspired Algorithm for the Problem" in the appendix to calculate an emigration rate that is proportional to the solution fitness and an immigration rate that is inversely proportional to the solution fitness, as illustrated by Figure 3.

Figure 3. BBO Migration Model

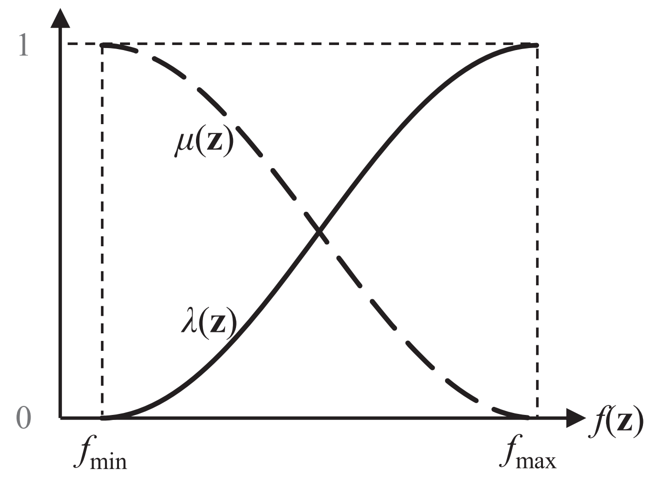


Table 1. Summary of Test Instances of the Collaborative Human–UAV Search Problem

No.	n	I_1	I_2	K_1	K_2	A	$\bar{d}$	T
1	10	1	1	2	4	9.6	1.5	30
2	10	1	3	2	4	9.6	1.5	30
3	20	1	2	2	4	21.0	3.9	30
4	20	2	3	2	4	21.0	3.9	30
5	27	1	2	2	4	21.0	3.5	60
6	27	2	3	2	5	21.0	3.5	60
7	46	1	3	3	4	38.3	4.1	90
8	46	2	5	3	5	38.3	4.1	90
9	56	2	2	3	5	43.6	3.9	120
10	56	2	5	3	6	43.6	3.9	120
11	88	2	5	3	5	95.2	3.6	240
12	88	4	6	3	6	95.2	3.6	240
13	106	3	8	3	6	133.5	4.2	360
14	152	5	10	3	6	170.9	4.6	480
15	193	6	12	3	6	224.8	5.3	720

Note. Here A is the area (in square kilometers) of the search map, d is the average distance (in kilometers) between subareas, and the search time T is in minutes.

4. For the search sequence of each team or UAV in each solution with a probability proportional to its immigration rate, immigrate features from the corresponding sequence in another solution selected with a probability proportional to the emigration rate.
5. Perform local search on some good solutions to enhance accuracy.
6. Replace stagnant solutions with randomly generated solutions to improve diversity.
7. Repeat steps 3 through 6 until the stopping condition is met (i.e., the computational time is used up).

In this way, the algorithm evolves the population toward the global optimal or a near-optimal solution by continually migrating features from probably high-fitness solutions to low-fitness ones. More detailed descriptions of the algorithm, including the pseudocode of the main algorithm and the greedy procedure, are given in the section "A Bio-Inspired Algorithm for the Problem" in the appendix.

Computational Experiments

We use 15 problem instances (Table 1), which are extended from the pure UAV search instances in Wang et al. (2017) to collaborate human–UAV search by adding human rescue teams, to test the proposed method. Note that these instances use identical UAVs and identical teams, which most practical applications use; however, our problem allows different UAVs and teams for generality. On the test set, we compare the proposed biogeography-based optimization (BBO) algorithm with the following five UAV search algorithms:

- A greedy algorithm in which each UAV uses a simple one-step look-ahead method (denoted as *Greed*; Bourgault et al. 2006).
- An algorithm based on a partially observable Markov decision process (denoted as *POM*; Waharte and Trigoni 2010).
- A PIO algorithm (Li and Duan 2014).
- An ACO algorithm (Perez-Carabaza et al. 2018).
- A hyperheuristic algorithm (denoted as *Hyper*; Wang et al. 2017).

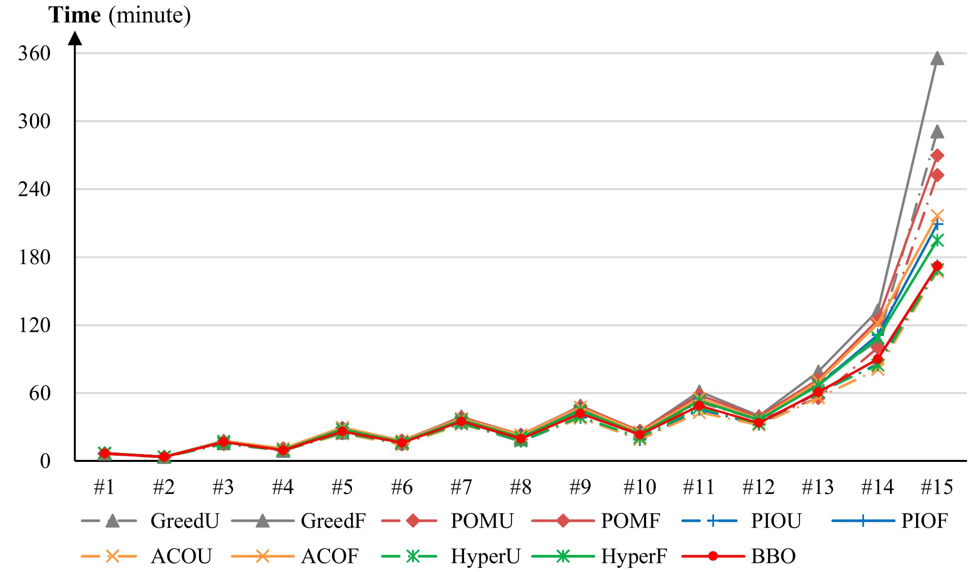
These methods were originally proposed for pure UAV search. We implement two versions for each of them: one uniformly regards all human teams as "slow UAVs" (denoted by a suffix "U" added to the algorithm name), and the other plans human team paths as lines 12–19 of Algorithm A.1 to make them move toward high-probability subareas close to the UAVs (denoted by a suffix "F").

For each instance, we perform a maximum of 500 simulation runs, each placing a target in a subarea selected based on its target location probability. The simulation is conducted on a computer with an i7-6500 2.5-GH central processing unit, a NVIDIA Quadro M500M card with 192 graphics processing unit

Table 2. Success Rates of the Algorithms on the Test Instances

No.	GreedU	GreedF	POMU	POMF	PIOU	PIOF	ACOU	ACOF	HyperU	HyperF	BBO
1	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
2	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
3	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
4	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
5	93.70	98.89	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
6	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
7	91.52	97.61	96.96	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
8	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
9	96.80	98.60	98.00	99.00	99.40	100.00	100.00	100.00	100.00	99.80	100.00
10	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
11	75.80	98.40	90.00	97.60	97.00	99.20	92.60	100.00	95.20	100.00	100.00
12	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
13	17.80	59.40	21.00	65.00	11.00	92.60	44.40	100.00	57.80	99.80	100.00
14	0.60	16.80	0.60	18.40	3.40	31.40	16.40	26.00	13.80	47.60	100.00
15	0.00	0.00	0.00	0.00	0.40	1.60	0.60	3.00	0.00	2.40	98.40

Figure 4. (Color online) Average Detection Times (in Minutes) of the Algorithms in the Test Instances

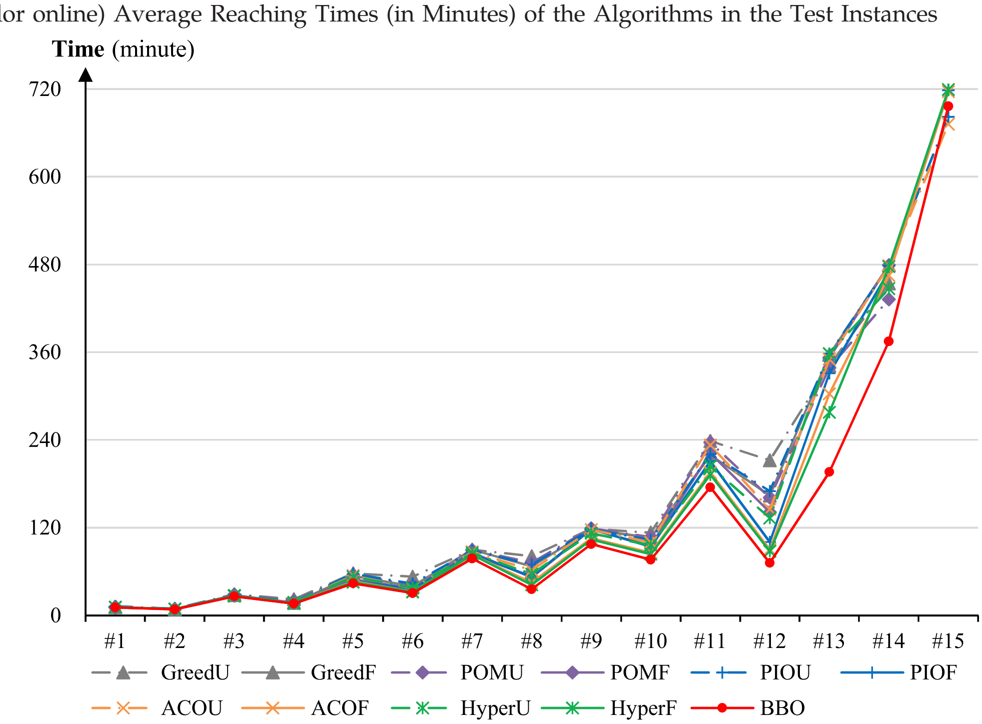


cores, and 8 GB of random-access memory. For a fair comparison, all the algorithms use the same running time of 10 minutes for problem instances 1–6 and 15 minutes for instances 7–15 because higher response times would be unacceptable in most emergency operations. The algorithm performance is evaluated in terms of three metrics: the success rate (i.e., the ratio of the number of runs in which the target is reached to the number of total runs, Table 2), the average detection times T_D (Figure 4), and the average reaching time T_R (Figure 5). The results show that

• In instances 1–4, which are small in size, all the algorithms achieve a 100% success rate, and there is no significant difference in either T_D or T_R.

• In instances 5–10, which are medium in size, most of the algorithms can achieve a 100% success rate. However, Greed and POM fail to reach the target occasionally; although the T_D values obtained by the proposed BBO algorithm are not the smallest (typically, smaller than the "F" versions but larger than the "U" versions of the other algorithms), the T_R values of BBO are always the smallest.

Figure 5. (Color online) Average Reaching Times (in Minutes) of the Algorithms in the Test Instances



• In the remaining instances, which are large in size, BBO can still achieve a success rate of 100% in instances 11–14 and 98.4% in instance 15, but most of the other algorithms fail to do so (in instance 12, all the algorithms have a 100% success rate because the number of teams and UAVs is relatively sufficient). In particular, in instances 14 and 15, in most simulation runs, the solutions of other algorithms cannot reach the target within the time limits. In terms of T_R, the performance advantage of BBO becomes more significant with increasing instance size (in instance 15, the T_R of BBO is not the smallest because the T_R values of the other algorithms are averaged over only a few successful runs).

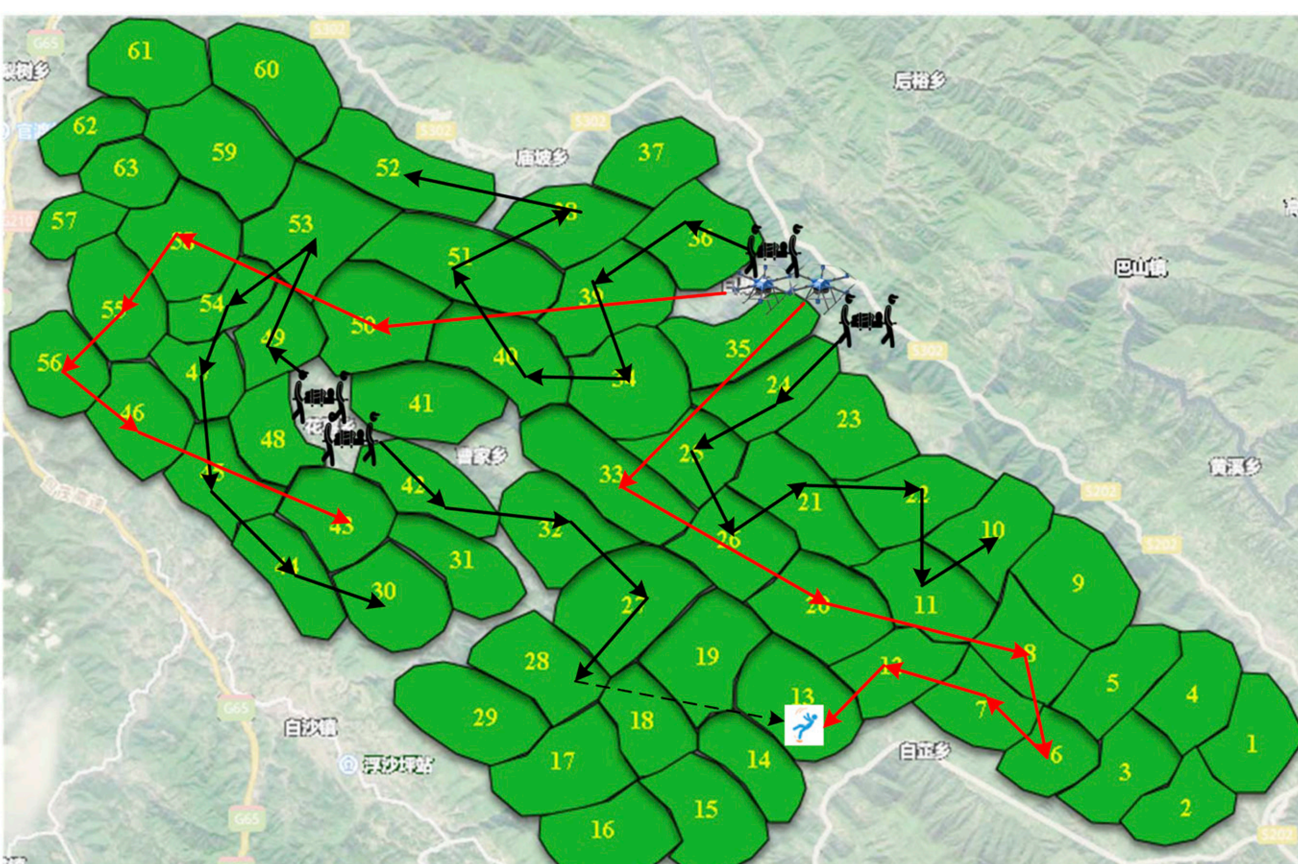
In summary, the proposed BBO exhibits the best performance among the algorithms. Although it does not always achieve the earliest detection time, it always achieves the earliest rescue time, which demonstrates its effectiveness in collaborative human–UAV search for ultimately reaching the target.

Real-World Applications

We have applied the proposed method to the Hua'eshan National Nature Reserve in Southwest China. The reserve has an area of 48,203 hectares (119,112 acres). Each year, tens of thousands of tourists visit the reserve, and some of them go missing. Through analysis of the terrain and the historical search experiences, we divided the reserve into 63 subareas and preconstructed an empirical model for estimating each subarea's initial target location probability based on the environmental features and the distance from the last place the tourist was seen. We provide details about estimating target location probabilities in the "Estimating the Prior Distribution on Target Location" section of the appendix. We also predefined a procedure for updating the probability distribution according to the previous search results and the predicted movement of the target. Consequently, when a new tourist-missing event is reported, we are able to quickly calculate the initial probability distribution and the subsequent probability updates and thus save significant preparation time for search path planning.

Our method was used to generate solutions for search and rescue of missing tourists in two cases. The first one was November 15, 2017. At 17:28, a 55-year-old man who had entered the reserve in the

Figure 6. (Color online) Search Paths of the UAVs and Human Teams in the First Real-World Operation



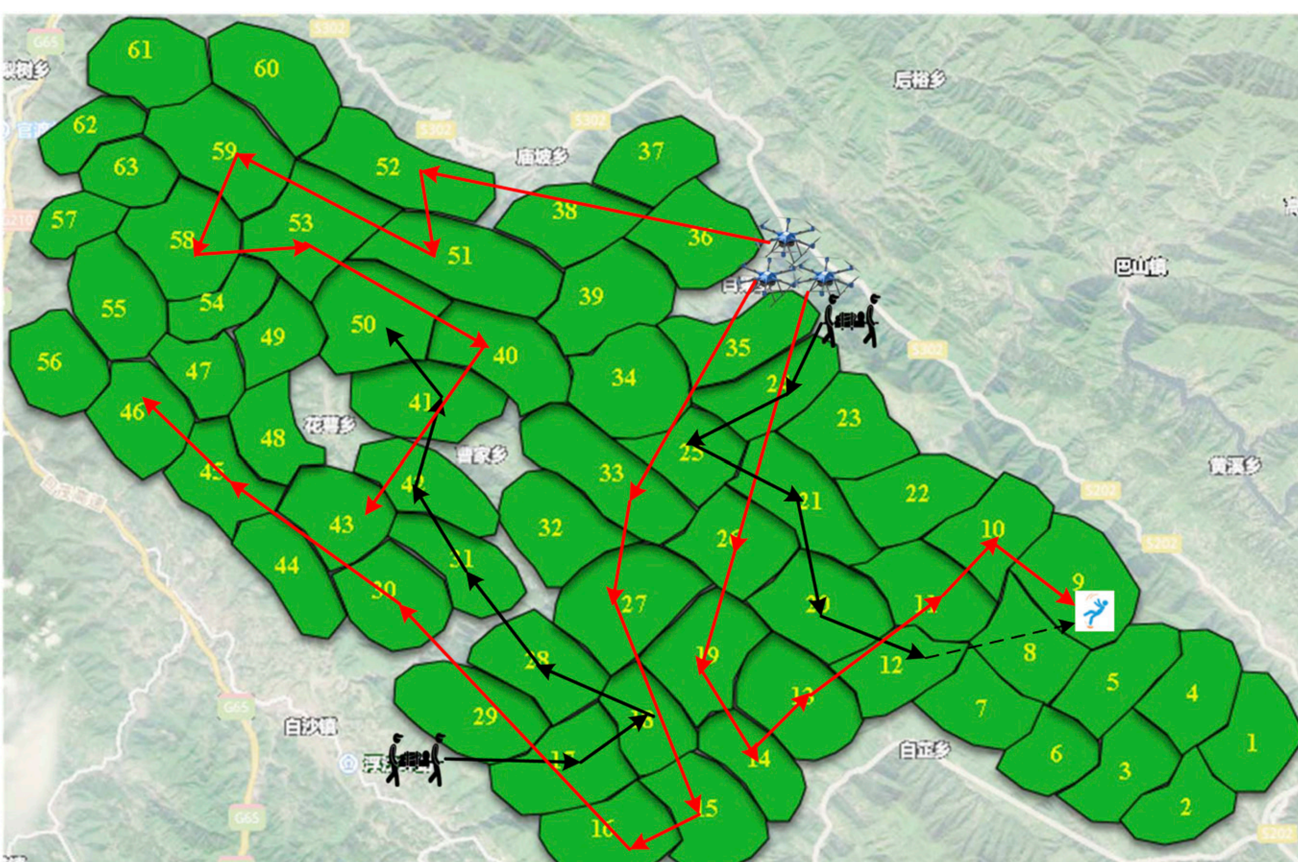
Note. For clarity, we draw only the paths that could be completed within the first 60 minutes of searching.

morning was reported to be out of contact. The administration office arranged two quad-rotor UAVs and four human teams and used the BBO algorithm to generate the search paths of the UAVs and teams (Figure 6). The preparation time was 24 minutes, including six minutes for program startup and problem instance construction, 15 minutes for algorithm execution, and 3 minutes for solution delivery. The search began at 17:53; after 48 minutes, a UAV detected the target in subarea 13 at 18:41, and the nearest team in subarea 28 took an additional 80 minutes to reach him at 20:02. The tourist was found seriously wounded, and the medical staff in the rescue team gave on-site emergency treatment and sent him to a hospital, where he recovered after two weeks. His doctor estimated that if the treatment had been delayed by more than 45 minutes, the tourist would likely have died.

The second case was on March 6, 2018. At 15:23, a group of university students, who had entered the reserve the day before, called the police and said that two classmates had lost contact with the group. The office used three UAVs and two human teams to search for the missing students based on the plan produced by our BBO algorithm. The preparation time was 22 minutes, including 4 minutes for program startup and instance construction, 15 minutes for algorithm execution, and 3 minutes for solution delivery. Figure 7 shows the planned paths. The search began at 15:45. After 59 minutes, a UAV detected the students in subarea 9 at 16:44, and the nearest team took an additional 47 minutes to reach them at 17:31.

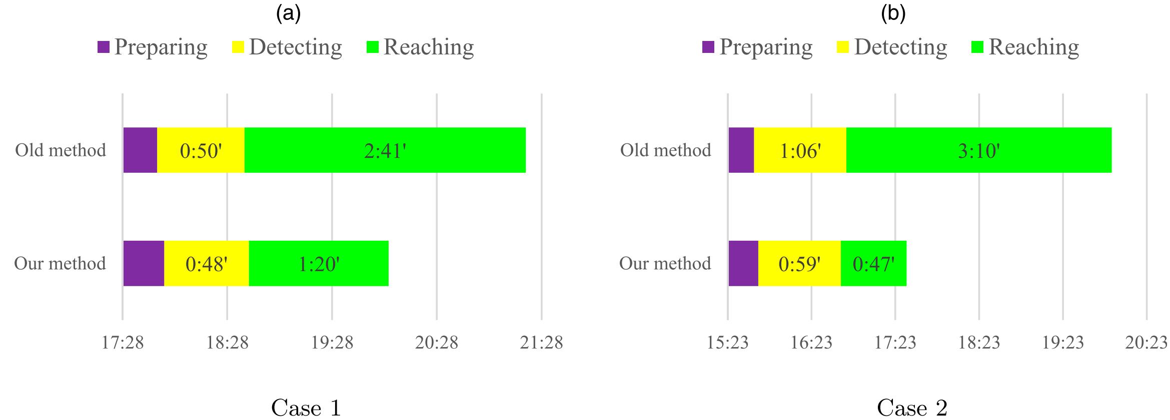
Later, for the two cases, we simulated the implementation of the solutions produced by the prior method used by the office, which allocates subareas to available UAVs in decreasing order of target location probability and constructs paths for human teams such that the total accumulated probability of paths is maximized (Liu et al. 2012). The results showed that in the first case, using the prior method would have taken about 50 minutes to detect the target and an additional 161 minutes to reach the target. In the second case, it would have taken about 66 minutes to detect the target and an additional 190 minutes to reach the target. Figure 8 compares the prior method with our method. Using our method, the time required to detect the target was shortened by 2 and 7

Figure 7. (Color online) Search Paths of the UAVs and Human Teams in the Second Real-World Operation



Note. For clarity, we draw only the paths that could be completed within the first 75 minutes of searching.

Figure 8. (Color online) Comparison of Our Method and the Method Used Previously for Two Real-World Operations



minutes and the total time required for reaching the target was shortened by 79 and 147 minutes in the two cases, respectively. Thus, our method greatly improved these life-critical operations.

Conclusion and Discussion

This paper presents a collaborative human–UAV search-planning problem, the objective of which is to minimize the expected time required to reach the target by human rescuers. We propose a simple yet efficient biogeography-inspired algorithm to solve the problem. Computational experiments and application to real-world operations demonstrate the performance of the proposed method. Although our applications involve searching for missing tourists in nature reserves, the approach can be used for target search in a variety of environments. Currently, we are cooperating with local police forces of more than 20 cities in China in deploying our approach for tasks such as searching for criminals and victims in suburbs and field environments. We also plan to extend the approach for humanitarian search-and-rescue operations (including multinational operations) in more countries.

From the experiments and applications, we identified the following limitations to be addressed in future studies:

- The time required for search plan preparation (including instance construction and solution generation and delivery) is still relatively long. For example, in the two real-world applications we discuss, the preparation time was approximately 22–24 minutes, and the time for mobilizing the teams and UAVs was approximately 16–18 minutes, which means that the teams and UAVs had to wait for about six minutes. Currently, we are developing a more intelligent user interface to simplify the process of instance construction and further improving the algorithm performance by better balancing global and local search (Zheng 2015) to shorten the response time.
- The estimation and update of target location probabilities depend on the environment. Thus, if the environment changes dramatically (e.g., a snowstorm occurs) during the operation, we may need to update the probability estimation model and regenerate the solution, which might significantly reduce the efficiency of the operation. One way to cope with this situation is to simultaneously generate some alternative solutions by taking possible changes into consideration (Zheng et al. 2014a).
- In general, for human teams, the estimation of their detection probabilities is relatively accurate, but the estimation of their travel and search times often deviates from reality. On the contrary, for UAVs, the estimation of travel and search times is more accurate than the estimation of detection probabilities. Our ongoing work also includes using fuzzy models (Liu 2007) to express the uncertainty of times and probabilities to improve the robustness of our method.

Appendix

Problem Formulation

Formally, the problem is to schedule I_1 human rescue teams and I_2 UAVs to search for a target in a wide area V, which is divided into n subareas. The target location is unknown, but we have a prior probability $p_v(0)$ of target location in each subarea $v \in V$. If the target is in v, the posterior probability that it will be detected by the team i searching the subarea with mode k is $p_h(i, v, k)$, where $1 \le i \le I_1$, $1 \le k \le K_1$, and K_1 is the number of human search modes. Typically, we consider two search modes of human teams; that is, $K_1 = 2$, where $k = 1$ denotes a detailed search and $p_h(v, 1)$ is assumed to be one and $k = 2$ denotes that the team simply passes through the subarea and $p_h(v, 2) \le 1$. Similarly, the posterior probability of being detected by the UAV i searching v with mode k is $p_u(i, v, k)$, where $1 \le i \le I_2$, $1 \le k \le K_2$, and K_2 is the number of UAV search modes defined according to different UAV altitudes and sensor operation modes. Without loss of generality, we assume that a smaller k indicates a more detailed search mode (and, hence, a higher detection probability). The symbols and explanations are given in Table A.1.

Table A.1. Nomenclature

I_1	The number of human rescue teams
I_2	The number of UAVs
V	The set of subareas
n	The number of subareas
K_1	The number of search modes of human rescue teams
K_2	The number of search modes of UAVs
$p_v(t)$	The probability that the target exists in subarea v at time t
$p_h(i,v,k)$	The detection probability of team i searching subarea v with mode k if the target is in v
$p_u(i,v,k)$	The detection probability of UAV i searching subarea v with mode k if the target is in v
$t_h(i,v,k)$	The time required by team i to search subarea v with mode k
$\triangle t_h(i,v,k,v',k')$	The time required by team i to travel from v with mode k to subarea v' with mode k'
$t_u(i,v,k)$	The time required by UAV i to search subarea v with mode k
$\triangle t_u(i,v,k,v',k')$	The time required by UAV i to travel from v with mode k to subarea v' with mode k'
$\mathbf{x}_i(t)$	The action of team i at time t, including the subarea searched and the search model used
$\mathbf{y}_i(t)$	The action of UAV i at time t, including the subarea searched and the search model used
T	The upper limit of the completion time of the operation
T^*	A hypothetical time at which the target is reached
$T_h^\dagger$	A hypothetical time at which the target is detected (and reached) by any human team
$T_u^\dagger$	A hypothetical time at which the target is detected by any UAV
T_u^*	A hypothetical time at which the target is reached by a team after it is found by a UAV

The dynamics of target existence depend on the target motion model, team actions $\mathbf{x}$, and UAV actions $\mathbf{y}$ and can be expressed as follows:

$$\mathbf{p}(t+1) = f_p\big(\mathbf{p}(t), \mathbf{x}(t), \mathbf{y}(t)\big), \tag{A.1}$$

where $\mathbf{p}(t) = \{p_1(t), \dots, p_n(t)\}$, $\mathbf{x}(t) = \{x_1(t), \dots, x_{I_1}(t)\}$ (each $x_i(t)$ defining in which subarea team i is located and which mode the team adopts), $\mathbf{y}(t) = \{y_1(t), \dots, y_{I_2}(t)\}$ (each $y_i(t)$ defining in which subarea UAV i is located and which mode the UAV adopts), $0 \le t \le T$, and T is the upper limit of the search time.

We are also given the time $t_h(i,v,k)$ for team i searching subarea v with mode k, the time $\triangle t_h(i,v,k,v',k')$ for team i traveling from subarea v with mode k to another subarea v' with mode k' ($1 \le v \le n; 1 \le i \le I_1; 1 \le k, k' \le K_1$), the time $t_u(i,v,k)$ for UAV i searching subarea v with mode k, and the time $\triangle t_u(i,v,k,v',k')$ for UAV i flying from subarea v with mode k to subarea v' with mode k' ($1 \le v \le n; 1 \le i \le I_2$; $1 \le k, k' \le K_2$). Normally, the larger the search time $t_h(i,v,k)$ or $t_u(i,v,k)$, the higher is the probability $p_h(i,v,k)$ or $p_u(i,v,k)$. The search mode may also have an effect on the travel time; for example, if a UAV searches v at a high altitude and searches v' at a low altitude, the travel time from v to v' (gliding) is less than that from v' to v (climbing). For simplicity, we omit the modes and write $\triangle t_h(i,v,v')$ or $\triangle t_h(i,v,\_,v',\_)$ in case the effect is trivial or k is indicated by the context.

The problem is to determine team actions $\mathbf{x}(t)$ and UAV actions $\mathbf{y}(t)$ ($0 \le t \le T$) so as to minimize T^*, the time at which the target is reached by (at least) a human rescue team. This can be divided into two cases: (1) the target is first detected by any human team at time $T_h^\dagger = T^*$, or (2) the target is first detected by any UAV at $T_u^\dagger < T^*$ and then reached by the nearest team after a time of $(T^* - T_u^\dagger)$.

In the first case, because the events of detecting the target by the teams are mutually exclusive, the probability of $T_h^\dagger = t$ for each time t ($0 \le t \le T$) can be iteratively calculated as

$$P(T_h^\dagger = 0) = 0, \tag{A.2}$$

$$\begin{aligned} P(T_h^\dagger = t) &= P(T_h^\dagger = t | T_h^\dagger \ge t \wedge T_u^\dagger \ge t) P(T_h^\dagger \ge t \wedge T_u^\dagger \ge t) \\ &= \left(\sum_{i=1}^{I_1} \sum_{v=1}^{n} \sum_{k=1}^{K_1} p_v(t) p_h(i,v,k|x_i(t)) \right) \\ &\quad \cdot \left(1 - \sum_{\tau=0}^{t-1} P(T_h^\dagger = \tau)\right) \left(1 - \sum_{\tau=0}^{t-1} P(T_u^\dagger = \tau)\right), \end{aligned} \tag{A.3}$$

where

$$p_h(i,v,k|x_i(t)) = \begin{cases} p_h(i,v,k) & \text{if } x_i(t) = (v,k) \\ 0 & \text{otherwise.} \end{cases} \tag{A.4}$$

Similarly, in the second case, the probability of $T_u^\dagger = t$ for each time t ($0 \le t \le T$) can be iteratively calculated as

$$P(T_u^\dagger = 0) = 0, \tag{A.5}$$

$$\begin{aligned} P(T_u^\dagger = t) &= P(T_u^\dagger = t | T_h^\dagger \ge t \wedge T_u^\dagger \ge t) P(T_h^\dagger \ge t \wedge T_u^\dagger \ge t) \\ &= \left(\sum_{i=1}^{I_2} \sum_{v=1}^{n} \sum_{k=1}^{K_2} p_v(t) p_u\big(i,v,k|y_i(t)\big) \right) \\ &\quad \cdot \left(1 - \sum_{\tau=0}^{t-1} P(T_h^\dagger = \tau)\right) \left(1 - \sum_{\tau=0}^{t-1} P(T_u^\dagger = \tau)\right), \end{aligned} \tag{A.6}$$

where

$$p_u\big(i,v,k|y_i(t)\big) = \begin{cases} p_u(i,v,k), & \text{if } y_i(t) = (v,k), \\ 0, & \text{otherwise.} \end{cases} \tag{A.7}$$

For the second case, we assume that when the target is detected by a UAV, it stops moving and waits for rescue. Let T_u^* be a hypothetical time at which the target is reached by a team after it is found by a UAV. Then $T_u^* = t$ indicates that the target is first detected by a UAV at $t' < t$ and reached by the nearest team after a period of $(t-t')$. Thus, we have

$$P(T_u^* = 0) = 0, \tag{A.8}$$

$$\begin{aligned} &P(T_u^* = t) \\ &= P(T_u^* = t | T_h^\dagger \geq t \wedge T_u^* \geq t) P(T_h^\dagger \geq t \wedge T_u^* \geq t) \\ &= P\Big(\exists t' < t : T_u^\dagger = t' \wedge \min_{1 \leq i \leq I_1} \Delta t_h(i, x_i(t), v, \_) = t - t'\Big) \\ &\quad \cdot P(T_h^\dagger \geq t) P(T_u^* \geq t) \\ &= \left(\sum_{t'=1}^{t-1} \sum_{i=1}^{I_2} \sum_{v=1}^{n} \sum_{k=1}^{K_2} p_v(t') p_u\big(i, v, k | \mathbf{x}(t'), y_i(t')\big) \right) \\ &\quad \cdot \left(1 - \sum_{\tau=0}^{t-1} P(T_h^\dagger = \tau)\right) \left(1 - \sum_{\tau=0}^{t-1} P(T_u^* = \tau)\right), \end{aligned} \tag{A.9}$$

where

$$p_u\big(i, v, k | \mathbf{x}(t'), y_i(t')\big) = \begin{cases} p_u(i, v, k), & \text{if } y_i(t') = (v, k) \text{ and } t - t' = \min\limits_{1 \leq i' \leq I_1} \Delta t_h(i, x_{i'}(t'), v, \_), \\ 0, & \text{otherwise.} \end{cases} \tag{A.10}$$

Combining the two mutually exclusive cases, we have $P(T^* = t) = P(T_h^\dagger = t) + P(T_u^* = t)$, and hence, the problem objective can be expressed as

$$\min E(T^*) = \sum_{t=1}^{T} t \cdot \big(P(T_h^\dagger = t) + P(T_u^* = t)\big). \tag{A.11}$$

A Bioinspired Algorithm for the Problem

The algorithm randomly initializes a population of solutions and then adds a potentially good solution produced by the greedy procedure to the population to accelerate the convergence of the algorithm. Algorithm A.1 presents the pseudocode of the greedy procedure, in which lines 4–10 give priority to UAVs that can search subareas of high probability within a short time and lines 12–19 make the teams move toward those subareas. Note that the next subarea of a UAV is chosen from the whole set V, and the next subarea of a human team is chosen from its neighborhood.

The main algorithm is based on the BBO metaheuristic (Simon 2008), which is inspired by the mathematical models of biogeographic distribution and evolution of species richness. The original BBO is for unconstrained global optimization problems. We adapt it to this complex discrete-time optimization problem and further introduce a local neighborhood structure (Zheng et al. 2014c) to the algorithm to avoid fast premature convergence and increase solution diversity. Algorithm A.2 presents the framework of the main algorithm, in which *rand*() creates a random number uniformly distributed in [0,1], η is a parameter that linearly decreases from $\eta_{\max}$ to $\eta_{\min}$ to control the probabilities of local and global migration, and $\widehat{g}$ is the maximum number of generations that a solution can keep in the population.

Each solution $\mathbf{z} = \{\mathbf{x}_1, \ldots, \mathbf{x}_{I_1}, \mathbf{y}_1, \ldots, \mathbf{y}_{I_2}\}$ consists of $(I_1 + I_2)$ parts, and each part is the sequence of subareas to be searched by the team/UAV. We calculate an immigration rate $\lambda(\mathbf{z})$ and an emigration rate $\mu(\mathbf{z})$ for $\mathbf{z}$ based on the sinusoidal migration model (Ma 2010) as

$$\lambda(\mathbf{z}) = \frac{1}{2} + \frac{1}{2} \cos\left(\frac{f_{\max} - f(\mathbf{z}) + \epsilon}{f_{\max} - f_{\min} + \epsilon} \pi\right), \tag{A.12}$$

$$\mu(\mathbf{z}) = \frac{1}{2} + \frac{1}{2} \cos\left(\frac{f(\mathbf{z}) - f_{\min} + \epsilon}{f_{\max} - f_{\min} + \epsilon} \pi\right), \tag{A.13}$$

where $f_{\max}$ and $f_{\min}$ are the maximum and minimum objective values in the population, respectively, and ϵ is a small constant to avoid a zero-division error such that $\lambda(\mathbf{z})$ is proportional to $f(\mathbf{z})$, whereas $\mu(\mathbf{z})$ is inversely proportional to $f(\mathbf{z})$, as illustrated in Figure 3.

Algorithm A.1 (Greedy Method for Collaborative Human–UAV Search Planning)

1. Let $t = 0$ and $k = 1$;
2. **repeat**
3. Let U_I be the set of all idle UAVs;
4. **while** $|U_I| > 0$ **do**
5. **for all** $i \in U_I$ **do**
6. Calculate $v_i^* = \arg\max_{v \in V}([p_v(t + \Delta t_u(i, v_i, v)) p_u(i, v, k)] / [\Delta t_u(i, v_i, v) + t_u(i, v, k)])$, where v_i is the current location of i;
7. **end for**
8. Let $i^* = \arg\max_{i \in U_I}([p_v(t + \Delta t_u(i, v_i, v_i^*)) p_u(i, v_i^*, k)] / [\Delta t_u(i, v_i, v_i^*) + t_u(i, v_i^*, k)])$;
9. Assign i^* to search $v_{i^*}^*$, remove i^* from U_I, and remove $v_{i^*}^*$ from V;
10. **end while**
11. Let H_I be the set of all idle human teams and V_S be the set of subareas to be searched by U_I;
12. **while** $|H_I| > 0$ **do**
13. **for all** $i \in H_I$ **do**
14. Let $V_N(i)$ be the set of neighboring subareas of the current location of team i;
15. Let $v_i^* = \arg\max_{v \in V_N(i)}(\max_{v' \in V_S} p_v(t + \Delta t_u(i, v_{i_{v'}}, v')) p_u(i_{v'}, v', k) / \Delta t_h(i, v, v'))$, where $i_{v'}$ is the UAV for searching v';
16. **end for**
17. Let $i^* = \arg\max_{i \in H_I}(\max_{v' \in V_S} p_v(t + \Delta t_u(i, v_{i_{v'}}, v')) p_u(i_{v'}, v', k) / \Delta t_h(i, v_i^*, v'))$;
18. Assign i^* to search $v_{i^*}^*$, remove i^* from H_I, and remove $v_{i^*}^*$ from V;
19. **end while**
20. Let T_C be the maximum search completion time of subareas in V_S;
21. **if** $T_C > T/(k+1)$ **then** $k \leftarrow k + 1$; **end if**
22. $t \leftarrow t + 1$, and update the status of the UAVs and teams;
23. **until** $t \geq T$ or $V = \emptyset$

Algorithm A.2 (BBO Algorithm for Collaborative Human–UAV Search Planning)

1. Randomly initialize a population of solutions
2. Use the greedy method to produce a solution and add it to the population
3. repeat
4. Calculate the migration rates of the solutions
5. **for all** solution $\mathbf{z}$ in the population **do**

6. **for** $i = 1$ to I_2 **do**
7. **if** $rand() < \lambda(\mathbf{z})$ **then**
8. **if** $rand() < \eta$ **then** select a neighboring $\mathbf{z}'$ with probability proportional to $\mu(\mathbf{z}')$
9. **else** select a nonneighboring $\mathbf{z}'$ with probability proportional to $\mu(\mathbf{z}')$
10. **end if**
11. Migrate from $\mathbf{y}'_i$ to $\mathbf{y}_i$
12. Perform the Nawaz-Enscore-Ham (NEH) method to reorder $\mathbf{y}_i$
13. **end if**
14. **end for**
15. **for** $i = 1$ to I_1 **do**
16. **if** $rand() < \lambda(\mathbf{z})$ **then**
17. **if** $rand() < \eta$ **then** select a neighboring $\mathbf{z}'$ with probability proportional to $\mu(\mathbf{z}')$
18. **else** select a nonneighboring $\mathbf{z}'$ with probability proportional to $\mu(\mathbf{z}')$
19. **end if**
20. Migrate from $\mathbf{x}'_i$ to $\mathbf{x}_i$
21. **end if**
22. **end for**
23. Resolve repeated search of subareas
24. Assign all unsearched subareas
25. **end for**
26. **if** the migrated solution is better than the original $\mathbf{z}$ **then**
27. **for all** $v \in V$ **do**
28. Obtain a neighbor $\mathbf{z}'$ by changing the search mode k of v to $k \pm 1$
29. **if** $\mathbf{z}'$ is better than $\mathbf{z}$ **then** $\mathbf{z} \leftarrow \mathbf{z}'$; **end if**
30. **end for**
31. **else if** $\mathbf{z}$ is not the current best solution and $\mathbf{z}$ has not been improved for $\widehat{g}$ generations **then**
32. Replace $\mathbf{z}$ with a new solution randomly generated
33. **end if**
34. **until** the stopping criterion is satisfied

Migration. We follow the work of Zheng et al. (2014c), which improves the original BBO by using a ring structure in which each solution has two neighbors. Based on the neighborhood structure, we define two migration operators: (1) local migration between neighboring solutions and (2) global migration between nonneighboring solutions. The latter is preferred in early stages for facilitating global search, and the former is preferred in late stages for enhancing local search (Zheng et al. 2014b). Migration performs differently on team and UAV search sequences:

• When migrating a team sequence $\mathbf{x}'_i$ in the emigrating solution $\mathbf{z}'$ to the corresponding team sequence $\mathbf{x}_i$ in the immigrating solution $\mathbf{z}$, we first obtain the set $V_C(i, i')$ of subareas in both $\mathbf{x}'_i$ and $\mathbf{x}_i$: if the set is empty, we set $\mathbf{x}_i$ as $\mathbf{x}'_i$; otherwise, we randomly select a $v \in V_C(i, i')$ and set the subsequence starting from v in $\mathbf{x}_i$ as that in $\mathbf{x}'_i$ while removing duplicated subareas from $\mathbf{x}_i$.

• When migrating a UAV sequence $\mathbf{y}'_i$ in $\mathbf{z}'$ to $\mathbf{y}_i$ in $\mathbf{z}$, we first obtain the set $V_D(i, i')$ of subareas in $\mathbf{y}_i$ but not in $\mathbf{y}'_i$ and the set $V'_D(i, i')$ vice versa and then randomly remove some subareas in $V_D(i, i')$ from $\mathbf{y}_i$ and add some subareas in $V'_D(i, i')$ to $\mathbf{y}_i$. Afterward, we employ the NEH method (Nawaz et al. 1983) to reorder all subareas in $\mathbf{y}_i$ such that it has the minimum total probability-weighted time.

For example, when migrating from $\mathbf{x}'_i = \{5, 8, 1, 2, 4\}$ to $\mathbf{x}_i = \{3, 2, 8, 6, 5\}$, we have $V_C(i, i') = \{5, 8, 2\}$. Assume that 8 is randomly chosen from $V_C(i, i')$; then subsequence $\{8, 1, 2, 4\}$ in $\mathbf{x}'_i$ is copied to $\mathbf{x}_i$ while the old 2 is removed. As a result, we obtain $\mathbf{x}_i = \{3, 8, 1, 2, 4\}$.

If migrating from $\mathbf{y}'_i = \{5, 8, 1, 2, 4\}$ to $\mathbf{y}_i = \{3, 2, 8, 6, 5\}$, we have $V_D(i, i') = \{3, 6\}$ and $V'_D(i, i') = \{1, 4\}$. Assume that 6 is randomly chosen from $V_D(i, i')$ and 1 is chosen from $V'_D(i, i')$; then $\mathbf{y}_i$ is set to a sequence that has the minimum total probability-weighted time among all permutations of $\{3, 2, 8, 5, 1\}$.

In spite of the different forms, the key idea of migration is to make the immigrating solution learn from the emigrating solution such that good solution components are more likely to be shared among the population. After migration, a solution may have some repeatedly searched subareas, for which we use the following strategies to improve the solution:

• For each subarea v searched by multiple UAVs, let $U(v)$ be the set of these UAVs and $t_{v,i}$ be the time at which UAV i completes the search of v. We select an $i^* = \arg\max_{i \in U(v)} \left(p_v(t_{v,i}) p_u(i, v, k)/t_{v,i}\right)$ as the UAV for searching v and remove v from the sequences of the other UAVs.

• For each subarea v searched by multiple teams, let $H(v)$ be the set of these teams and $t_{v,i}$ be the time at which team i completes the search of v. We select an $i^* = \arg\max_{i \in H(v)} \left(p_v(t_{v,i}) p_h(i, v, k)/t_{v,i}\right)$ as the team for searching v and remove v from the sequences of the other teams (but the teams can still pass through v without searching it).

Finally, we sort all unsearched subareas (if they exist) in decreasing order of the target location probability and then assign each of them to a team or a UAV such that the subarea can be searched as early as possible.

Local Search. To enhance solution accuracy, we also perform a local search on each new offspring $\mathbf{z}$ that is better than its parent. The operator produces at most $2n$ neighbors of $\mathbf{z}$, each being obtained by changing the search mode k of a subarea $v \in V$ to $k \pm 1$ (subject to k not exceeding the range). The best neighbor, if better than $\mathbf{z}$, replaces $\mathbf{z}$ in the population.

Estimating the Prior Distribution on Target Location

To estimate a prior probability $p_v(0)$ of the target being located in each subarea v at time $t = 0$, we first estimate a value $\alpha_v(0) \in [0, 1]$ based on the terrain of subarea v and the weather conditions at time 0. The more suitable the terrain features and the weather conditions are for travel, the higher $\alpha_0(v)$ is. Next, we assume that the target is moving from the last seen place v_0 to v and calculate a basic distance $d^*(v_0, v)$ that the target is most likely to travel from v_0 to v as follows:

$$d^*(v_0, v) = \nu(v_0, v) t_0 \,, \tag{A.14}$$

where t_0 denotes the time passed since the report of the missing tourist, and $\nu(v_0, v)$ is the estimated average speed of the target from v_0 to v during the period $[0, t_0]$.

Let $d(v_0, v)$ be the distance from v_0 to v; if $\Delta d_v(0) = d(v_0, v) - d^*(v_0, v)$, then $p_v(0)$ is estimated as follows:

(1) If $\Delta d_v(0)$ is larger than an upper limit d^U, then the target cannot move to v within t_0, and thus, $p_v(0) = 0$.

(2) Otherwise, $p_v(0)$ follows a normal distribution with mean zero and variance proportional to $|\Delta d_v(0)|/\alpha_0(v)$ and is calculated as

$$p_v(0) = c \cdot \mathcal{N}\left(0, \frac{b \cdot |\Delta d_v(0)|}{\bar{d} \cdot \alpha_0(v)}\right), \tag{A.15}$$

where $\bar{d}$ is a coefficient related to the size of the search area, and c is a coefficient that is adjusted to ensure that the total probability equals 1.

During the search operation, we need to update not only $p_v(t)$ in a manner similar to Equation (A.15) but also the estimated speed of the target (as the target's physical strength diminishes), the value of $\alpha_v(t)$ (with the change in weather conditions), the place last seen (if new information about the target is provided), and the coefficient c (to ensure that the total probability still equals 1). In particular, if a team or UAV i has completed the search of a subarea v at time t but has not detected the target, the location probability $p_v(t)$ should be updated as $p_v(t)(1 - p_h(i, v, k))$ or $p_v(t)(1 - p_u(i, v, k))$. However, in the current implementation of our algorithm, we simply remove a searched subarea from the set V because the detection probabilities are usually high, and the subsequent rescheduling needs to be completed in a shorter time.

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