A Fast Algorithm for Scheduling Detection-and-Rescue Operations Based on Data from Wireless Sensor Networks

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Abstract. The need for the search, detection and rescue of disaster survivors arises in many emergency situations in military and civil applications. Suppose a number of people are trapped in ruins after an earthquake or tsunami. Their medical condition depends on their location, detection time and the time of the rescue operation. In order to efficiently detect and perform the needed rescue operations, a network of wireless sensors is used which provide acoustic, seismic, electromagnetic, gravimetric and other information. The information is processed automatically to yield prior probabilities of location and expected rescue times for each potential target. The acquired information from the sensors is imperfect because under extraordinary and severe circumstances, two types of errors may occur: (i) a "false-negative detection test" – it is a case when a target is overlooked during the test; and (ii) a "false-positive detection", or "false alarm" – when a not-a-target location is wrongly classified as a sought target. Therefore, non-zero probabilities of overlooking a hidden target and a "false alarm" exist. We suggest a two-phase solution to the problem of scheduling detection and rescue operations. First, the disaster area is divided into sub-areas and available rescue teams and sensors are assigned. Second, a schedule is found for the rescue teams to perform the rescue operations (in parallel). We seek to find the best coverage of the disaster sub-areas served by rescue teams and to schedule the search-and-rescue operations in each sub-area while minimizing the search-and-rescue time and maximizing the number of saved lives within a given search time limit. The problem is formulated as a non-standard two-stage assignment / scheduling problem and a fast combinatorial real-time algorithm is suggested.

Keywords: disaster management, detection-and-rescue problem, wireless sensor network, imperfect inspections, best coverage, scheduling, fast on-line algorithm

1 Introduction

The need for search, detection, and rescue (DAR) of disaster survivors arises in many emergency situations in military and civil applications. Suppose that a large number of people are trapped in ruins after an earthquake, a tsunami wave, or a terrorist attack. Their medical condition and survival probabilities depend on their location, the time needed to locate them and the evacuation (rescue) time. For DAR operations to be efficient, a computer-aided network of wireless sensors of different types is used which provide acoustic, seismic, electromagnetic, gravimetric and other information about the targets (see [6, 11, 17]).

Real-time monitoring and quick response are the most essential requirements in the design of an emergency response system. Different types of sensors are used together and the collected information is incorporated into a wireless sensor networks (WSNs) thus allowing for the communication between both sensors and human rescue teams. For example, temperature and movement-detection sensors are used to monitor the location of people, satellite cameras can track the spread of the disaster and depict the disaster area map while ultrasonic sensors measure the range to targets in the environment and report dynamic changes of maps due to the changes of built structures through destruction of debris. The use of such heterogeneous tools must be supported by innovative planning or scheduling tools in order to exploit and integrate the capabilities of each sensor and provide an optimal use of all available resources.

In this work, we consider scenarios that require locating and identifying multiple stationary and dynamic targets. We assume the presence of a relevant communication infrastructure enabling the command center and the rescue teams to continuously exchange information. In order to plan an effective team deployment over the search area, it is necessary to rapidly gather as much information as possible about the targets and the area, and use this information to define joint search-and rescue mission plans. A mission plan consists of a sequence of actions to be performed by an agent for a certain time duration as defined by environmental factors and geographical locations.

Mission planning is modeled as a mixed integer linear programming problem (MILP) in which the model simultaneously allocates predefined sub-areas of a disaster area to be explored and specifies the schedule of the actions that each agent should follow. The resulting plans guarantee optimal results for the search activities. A number of constraints are included to model cooperation and connectivity relationships among agents (sensors and human rescue teams). For example, at the beginning of the search process, the agents are uniformly spread over the area, while in later stages they are focused on specific subareas according to importance.

Initially, the data from the sensors is collected by the network and integrated to define prior probabilities of location, the damage scale and expected rescue times for each potential target. The problem presented in this paper can be partitioned into two stages. First, the disaster area is divided into sub-areas and available rescue teams are assigned to each sub-areas in which they will perform in parallel their DAR missions. At the second stage, a detailed schedule of operations is planned ahead for each rescue team. Notice that the detection-and-rescue operations at the second stage are implemented simultaneously by several rescue teams. The goal is to find the best coverage of the disaster area by mobile rescue teams and to schedule the search-and-rescue operations in each sub-area in order to minimize the search-and-rescue time and maximize the number of saved lives within the given limits of the search-and-rescue time. This problem is a natural extension of similar search-and-rescue problems studied in [7-9, 11, 13, 16].

The automatic information-gathering system gathers information from sensors scattered over a geographical region to help the rescue teams to find the targets in minimum time. The inspections are imperfect because under uncertain environmental circumstances, two types of errors may occur: (i) a "false-negative” detection test – a target object is overlooked during the test; and (ii) a "false-positive” detection or a "false alarm", which wrongly classifies a clean location as a sought target. Hence, non-zero probabilities of overlooking the hidden target as well as that of a "false alarm" exist. We propose to model the DAR problem as a scheduling problem involving several search teams working in parallel, and subject to time/budget and probabilistic constraints. The general problem of selecting the best schedule is NP-hard thus, the proposed solution is an approximation or an “almost-optimal” solution.

The remainder of the paper is organized as follows. In Section 2, we provide a review of related works and approaches for using smart sensor networks to detect/rescue hidden objects while focusing on detecting and rescuing of human survivors. In Section 3, we provide a formal formulation of the problem and propose a mathematical model. In Section 4 we propose a solution using a fast algorithm (without significant computational load). A numerical example is given in Section 5 and Section 6 contains a summary along with future research directions.

2 Related Work

Planning of search-and-detection operations has been researched thoroughly in the area of operational research and artificial intelligence. The pioneer work done by Bernard Koopman done during World War II aimed to provide efficient methods for detecting hidden submarines. See [2], [15] and [19] for a detailed survey and the bibliography of the discrete search literature. In recent years, the problem of planning and scheduling of detection operations has become critical in light of increasing growth of natural and human-made disasters and the usage of a WSN has become popular. A WSN is an advanced technology for collecting diverse data from multiple sensors. A typical WSN system is distributed within the sensor field and consists of a number of sensor nodes, such as seismic, acoustic and magnetic anomalies. See [1] for a comprehensive survey regarding the main factors influencing the WSN design. The WSN collects thousands of raw data and works as a centralized or decentralized fusion system (see [18]). In the centralized case, the data is collected by individual sensors and sent through the sink node to a central dedicated fusion node, task manager node for processing while in the decentralized case the information is collected and analyzed by a set of autonomous devices.

We consider a situation where the basic functions of the WSNs are to monitor and control environmental parameters related to the detection-rescue and collectively transfer the data obtained through the network to a central location. In WSNs, the mobile agents are added into the system to improve its performance and act as automatic carriers of data. [4] provides more examples and details of modern applications of WSNs including battlefield surveillance, detection of enemy intrusion and detection and rescuing of hidden targets. Many search-planning algorithms are based on a cellular partitioning of the disaster area (see [7] and the references within). In [3], a multi-scale grid is used for representing the environment. [10] studied the usage of UAVs (unmanned aircraft vehicles) for DAR missions. Other research has studied the use of autonomous teams of robots for DAR (see [14]). MILP models has been successfully used in search planning problems and mission assignment ([5]). An advantage of a MILP formulation is that, given exact input data, an optimal solution can be provided. Compared to latter works, we put an emphasis on the parallel work of several search-and-rescue teams and solve both task allocation and scheduling problems.

To conclude, we consider a different objective function and corresponding mathematical formulations of the problem. This problem is a natural extension of similar search-and-rescue problems studied in [7-9, 11, 13, 16]. Our contribution is threefold: (i) a new two-stage decomposition methodology partitioning the initial mission planning problem into an assignment and scheduling components aimed to enhance the efficiency of DAR missions performed by several teams of networked agents (sensors and human teams); (ii) a novel generalized assignment problem (used at the first stage) including disjunctive and resource constraints in the context of DAR missions; (iii) a novel scheduling problem (of the second stage) and the design of a new fast scheduling algorithm.

3 Problem Description and Mathematical Formulation

As said above, the goal of the present study is two-fold. First, we find the best coverage of the disaster area by a mobile rescue teams and, second, we optimally schedule the search-and-rescue operations in each sub-area in order to minimize the search-and-rescue time and maximize the number of saved lives within the given limits of the search-and-rescue time. At the first stage, the disaster area is divided into sub-areas and available rescue teams are assigned to the disaster sub-areas in which they will perform in parallel their DAR missions. At the second stage, a detailed schedule of operations is planned ahead for each rescue team. The DAR operations at the second stage are implemented simultaneously by several rescue teams.

3.1 The coverage of the Disaster Area

The planning process starts with discretizing the known disaster area into a set of squared environmental cells representing the spatial elements that should be served by the available WSN and the rescue teams. Without loss of generality, the disaster area is decomposed into a uniform cell grid, the cells' set being denoted by A, $|A| = n$. In this simple, but effective scenario, the disaster area is uniformly partitioned in as much equal sub-areas as possible within the available time reserve and personnel resources. In real-world scenarios, the disaster area is usually irregular and cluttered; we represent the non-uniform effect on both mobility/effectiveness of the rescue teams, on the one hand, and sensing of the WSN throughout the field, on the other. For this purpose, we assume that the total number of available human teams is known and equals M while the total number of available sensors is denoted by S .

We are now ready to formulate the area coverage-planning problem as a generalized assignment problem with resource and precedence constraints. As will be seen next, the problem is a special case of the MILP class.

Define, f_{hj} - performance effectiveness function, corresponding to a human rescue team h, $h = 1, 2.., m$, assigned to perform the detection-and-rescue missions in cell j, $j = 1, 2.., n$. f_{hj} is characterized by the expected number of detected/saved human lives during performing the DAR mission (in cell j) which, in turn, depends on the local sub-area characteristics, the agent skills and the search time. Therefore, the entire performance of the mission planning for the effective coverage by the agents strictly depends on the allocation of the agents to the sub-areas. These characteristics are estimated by the rescue/evacuation manager based on the data provided by the WSNs. This issue is particularly relevant in the case of the heterogeneous sensors and teams working simultaneously ("in parallel"). We take into account disjunctive conditions stating that each cell can be served by a human team and/or by an automated device, like a mobile robot or an unmanned aerial vehicle UAV. Precedence relations are imposed according to which, in any cell, first the sensors measurements are to be performed, after which human teams are able to start their rescue mission.

In addition, define B and T the total budget at hand and the total time for the DAR operation respectively and by c_{hj}, t_{hj} and d_{hj} the cost, the required time, and sensor cost required to perform a DAR in cell j by team h. Also, let k_j be the number of rescue teams in sub area j (can be larger than 1). Finally, let X_{ij} and Y_{sj} be binary variable defined as follows:

$$X_{ij} = \begin{cases} 1 & \text{rescue team } i \text{ assgined to cell } j \\ 0 & else \end{cases}$$

and

$$Y_{sj} = \begin{cases} 1 & \text{sensor } s \text{ is assgined to cell } j \\ 0 & else \end{cases}$$

Then the constrained multi-agent coverage problem (CMACP) can be formulated as presented in (1)-(7).

$$\max \sum_{h=1}^{m} \sum_{j=1}^{n} f_{hj} \cdot x_{hj}$$

subject to

$$\sum_{h=1}^{m} \sum_{j=1}^{n} x_{hj} \leq M \quad (1)$$

$$\sum_{h=1}^{m} \sum_{j=1}^{n} c_{hj} \cdot x_{hj} \leq B \quad (2)$$

$$\sum_{h=1}^{m} \sum_{j=1}^{n} d_{hj} \cdot y_{hj} \leq C \quad (3)$$

$$\sum_{h=1}^{m} \sum_{j=1}^{n} t_{hj} \cdot x_{hj} \leq T \quad (4)$$

$$\sum_{h=1}^{m} x_{hj} \leq k_j \quad (5)$$

$$\sum_{h=1}^{m} x_{hj} = 1 \quad (6)$$

$$x_{hj} \leq y_{kj}, \forall k, h, j \quad (7)$$

$$x_{ij}, y_{kj} \in \{0, 1\}, \forall k, h, j, i$$

The first constrain is immediate since there is a total of M teams while (2)–(4) represent the total budget of the human teams, the total budget of the WSN system and the total time given to perform the rescue operation. (5) follows from the definition of k_j and (6) corresponds to the fact that every rescue team should be assigned to a sub area. Since sensor measurement must precede the rescue mission in all sub-areas, we have (7).

The presented generalized assignment problem with precedence and resource constraints is a special class of the MILP problem. We have used the MILP solver (a commercial optimization package called GAMS) and obtained an optimal solution in under 5 minutes for small and medium size instance $(m \leq 20, n \leq 100)$.

3.2 The Scheduling of Detection-and-Rescue Operations in Each Sub-Area

After completing phase 1, i.e., assigning the agents to the different sub area (cells) we can continue to phase 2 and define the sequence of detection-and-rescue operations. When defining the sequence of operations, the most important goal is to maximize the number of saved human survivors (targets) and then protection of property.

We consider the following scenario. The targets are clustered, that is, located in groups of linked sites (cells) where the targets in each cluster are processed simultaneously while each group is inspected and rescued non-stop from one cluster to the other. Since the coverage of the area into the cells is sufficiently fine-grained, we may assume that each cell contains one target (at the most). If the number of rescue teams is K (known in advance since it is defined by the resource constrain), a cluster of K targets can be processed simultaneously. At the first step we determine the cluster of size K that contains the maximum of expected number of potential survivors in its cells (and will be processed by K rescue teams). After the first cluster is processed, the K teams are assigned to the next cluster (again, containing K targets). The targets are detected and rescued until the given time reserve T_0 is exhausted, or all targets are discovered and saved. The problem is to efficiently detect and rescue the targets so as to maximize the possible performance (the number of saved lives) of the detection-and rescue mission.

For simplicity, we consider the following special case of scheduling the human rescue teams, the scheduling of automated search teams and heterogeneous smart sensors being handled along the same line. Any inspection of any cell (either containing the target or not) is imperfect. This means that a prior probability α_i of a false alarm and a prior probability β_i of overlooking the target are given. This implies that each cell may be examined more than once. It follows that a detection sequence will be finite but repetitions of the same cells are possible. Each rescue team performs a set of sequential operations in order to identify and rescue the target. The times and expected efficiency of lifesaving during the operations being given, the goal of the detection and rescue process is to determine a search strategy which the rescue team employs to locate and rescue the maximum number of targets within the given reserve of detection-and-rescue time.

A disaster area contains m squared sub-areas. Each are contains mi potential target locations, $m_i<m$, $i=1,2,...,N$ and is characterized by the following known parameters:

- p_i - prior probability that location i contains the target;
- α_i - prior probability of a "false alarm" , or a false-positive outcome, the conditional probability that an inspection declares that a target is found in cell i whereas, in fact, this location does not contain a target;
- β_i - prior probability of overlooking, or a false-negative outcome, the conditional probability that an inspection declares that location i has no target but in fact it has;
- t_i - expected time to inspect cell i by one of the teams
- c_i - expected number of potential survivors in cell i.

Each sequential inspection strategy specifies a finite sequence

$$s = \langle S[0], s[1], s[2], \ldots, s[n], \ldots \rangle$$

where s[n] denotes the cluster's index which is inspected by K parallel teams at the nth step of sequence s, s[n]$\in${1,2,...} and s[0] is an initializing sub-sequence of locations which will be defined below.

Given the above input data, the optimal search scenario is specified by the following conditions:

i. the clusters are inspected sequentially;
ii. for any search strategy and any cluster, the outcomes of inspections are independent;
iii. the stopping rule is defined as follows:

For any integer h, define - a_{ih} - the conditional probability that cluster i contains the target given that it contains the target in h inspections. a_{ih} depends on the given p_i, β_i. In addition, let H_i ("height") be the minimal positive integer such that $a_{ih} \geq CL$ where CL is a priori given confidence level. It should be noted that all of the H_i's can be computed by the rescue manager before the search process starts.

Given a sequence *s* of inspections, the search ends when either the search-rescue time reserve expires, or, at some step, all clusters return the outcome of "*the target is claimed to be in location* i *for the* H_i^{th} time in s".

For a given sequence s , we shall use the following notation:

– $T_{s[n]} = T\left(s[n], s\right)$ – time (accumulated) spent to detect the target in $s[n]$ on the n^{th} step of strategy s;
– $T_{s[n]} = \max_m t_{s[m]}$ where maximum is taken over all the teams working in cell;
– $P_{\underline{s}[n]}$ -the probability that targets, located in cell $s[n]$, are detected $H_{s[n]}$ times before the n^{th} step of strategy s . $H_{s[n]}$ and $P_{\underline{s}[n]}$ depend on α_i and β_i , and guarantee required confidence level; in practice, $H_{s[n]}$ is equal 1 or 2. This concept and its relationship with the confidence level CL is described below.
– $c_{s[n]}$ – lifesaving efficiency in location (cluster) $s[n]$.

The expected (linear) total lifesaving efficiency, $F(s)$, is defined as follows:

$$\max \qquad F(s) = \sum_{n=1}^{\infty} P_{s[n]} c_{s[n]} T_{s[n]}$$

subject to .

$$T_{s[n]} \le T_0$$

In the above notation, the stochastic scheduling problem is to find a sequence s^* that maximizes the expected efficiency $F(s)$ subject to the search time reserve.

One should note that the above formulation gives rise to three special cases: when $\alpha_i = \beta_i = 0$ for every i , the problem is known as the perfect inspections problem researched in the finite-horizon scheduling literature. If all α_i 's are zero but $\beta_i \neq 0$ for all i's we have the false-negative inspections and if $\alpha_i \neq 0, \beta_i = 0$ for every i we have the false-positive inspections. In addition, when the problem is minimization, and the time reserve constrain is relaxed, the model is much simpler and can be solved using a proposed method in [12].

4 Problem Analysis and Algorithm

We begin by defining

$B_i = \{\text{Inspection declares that cluster } i \text{ has a target}\}$,
$C_i = \{\text{Cluster } i \text{ really contains the target}\}$

and using the notations in Section 3 we have $p_i = P(C_i)$, $\alpha_i = P(B_i | \overline{C_i})$ and $\beta_i = P(\overline{B_i} | C_i)$.

Now, the probability that the target is discovered in cell i, defined f_i, is equal to

$$f_i = P(B_i) = P(C_i)P(B_i / C_i) + P(\overline{C}_i)P(B_i / \overline{C}_i) = p_i \cdot (1-\beta_i) + (1-p_i)\alpha_i,$$

while the probability to correctly detect the target in cell i within a single inspection is equal to

$$P(C_i / B_i) = \frac{P(C_i)P(B_i / C_i)}{P(C_i)P(B_i / C_i) + P(\overline{C}_i)P(B_i / \overline{C}_i)} = \frac{p_i \cdot (1-\beta_i)}{p_i \cdot (1-\beta_i) + (1-p_i)\alpha_i}$$

Theorem 1. Given a sequence s, the conditional probability a_{ih} - the probability that location i contains the target given the probability it contains the target in h inspections is given by:

$$a_{ih} = P\left(C_i / B_i^{(1)} \cap B_i^{(2)} \cap \ldots \cap B_i^{(h)}\right) = \frac{P(C_i) \cdot P\left(B_i^{(1)} \cap B_i^{(2)} \cap \ldots \cap B_i^{(h)} / C_i\right)}{P\left(B_i^{(1)} \cap B_i^{(2)} \cap \ldots \cap B_i^{h}\right)}$$

$$= \frac{p_i \cdot (1-\beta_i)^h}{p_i \cdot (1-\beta_i)^h + (1-p_i)\alpha_i^h}$$

Corollary. Given a predetermined confidence level CL for the probability a_{ih} defined above, H_i is the minimal integer satisfying

$$a_{ih} = \frac{p_i \cdot (1-\beta_i)^{H_i}}{p_i \cdot (1-\beta_i)^{H_i} + (1-p_i)\alpha_i^{H_i}} \geq CL \quad \text{for any } i.$$

Inspections in each cluster M_i are done in parallel by different rescue teams in pre-specified times. The search strategy is a finite sequence of clusters (more exactly, their index), where, at step n, the cluster $s[n]$ is inspected and rescued:

$$s = \langle S[0], s[1], \ldots, s[n], \ldots \rangle .$$

Denote by $s[k,n]$ the number of a cell in cluster $s[n]$ inspected at the nth step of strategy s. Denote by $s^*[k,n]$ the total number of inspections of cell $s[k,n]$ counting from the first inspection up to its inspection in cluster $s[n]$ inspected at the n^{th} step of strategy s. Notice that $s^*[k,n]$ can be easily computed for all k as soon as the sequence s is known up to its n^{th} step. Denote by $c_{s[k,n]}$ the rescue effectiveness assigned to cell $s[k,n]$. Let $T_{s[k,n]}$ be the time spent for inspection of all cells of all the clusters in strategy s up to location $s[k,n]$,

$$T_{s[k,n]} = \sum_{i=1}^{N} t_i (H_i - 1) + \max T_{[m,s]} + \sum_{i=1}^{k} t_{s[k,n]},\ n \geq 1$$

The search effectiveness attributed to strategy s is

$$F(s) = Exp(R(s)) = \sum_{n=1}^{\infty} \sum_{k=1}^{j_k} R_{s[k,n]}(s) \cdot P\left(R(s) = R_{s[k,n]}(s)\right) =$$
$$= \sum_{n=1}^{\infty} \sum_{k=1}^{j_n} c_{s[k,n]} T_{s[k,n]} \binom{s^*[k,n]-1}{H_{s[k,n]}-1} \left(1 - f_{s[k,n]}\right)^{s^*[k,n]-H_{s[k,n]}} \cdot f_{s[k,n]}^{H_{s[n]}}$$

Theorem 2. The strategy s^* is an optimal strategy for the max-efficiency search problem iff the ratios

$$Q_{s[n]} = \frac{\sum_{k=1}^{j_n} c_{s[k,n]} \cdot P_{s[k,n]}}{T_{s[n]}} = \frac{\sum_{k=1}^{j_n} c_{s[k,n]} \cdot P_{s[k,n]}\left(s^*[k,n]\right)}{T_{s[n]}}$$
$$= \frac{\sum_{k=1}^{j_n} c_{s[k,n]} \cdot \binom{s^*[k,n]-1}{h_{s[k,n]}-1} \left(1 - f_{s[k,n]}\right)^{s^*[k,n]-h_{s[k,n]}} \cdot f_{s[k,n]}^{h_{s[k,n]}}}{T_{s[n]}}$$

are arranged in non-decreasing order of the magnitude.

The proof is by the interchange argument and skipped here.

5 Example

Consider the problem of searching a target in a stochastic setting described in [3]. The rescue team has limited time (to perform the search and rescue operation) and limited memory (the only saved information is the information on how many times a target has been detected in each visited cell up to a current step in the search sequence). The search stops as soon as the limit of the search time is exhausted. The area of interest is divided into N possible locations containing the hidden targets. In our example, we consider an area divided into four sub-areas with one cell in each ($M = \{c_1, c_2, c_3, c_4\}$) two teams ($K = 2$) and $T_0 = 24$ (hours). In addition, there are three clusters,

$C_1 = \{c_1, c_2\}$, $C_2 = \{c_3, c_3\}$ and $C_4 = \{c_3, c_4\}$. The input data is given in Table 1 below and the confidence level is 95%.

Table 1. Input Data

Cells	c_1	c_2	c_3	c_4
$p_i = P(C_i)$	0.5	0.6	0.75	0.01
$\alpha_i = P(B_i \vert C_i)$	0.07	0.10	0.12	0.10
$\beta_i = P(\overline{B}_i / C_i)$	0.03	0.07	0.05	0.04
t_i	5	8	10	10
c_i	20	10	12	2

Using Table 1 and (1)-(2) we can compute f_i and H_i for $i = 1, 2, 3, 4$. For example, for the first cell ($i = 1$), we have $f_1 = 0.52$, $a_{11} = 0.932692$ and a_{12} is equal to 0.994819. Following, H_1 equals 2 for a CL of 95%.

Table 2 below presents the values of f_i and H_i for all four cells.

Table 2. Computation of f_i and H_i

Cells	c_1	c_2	c_3	c_4
f_i	0.52	0.618	0.8025	0.0106
H_i	2	2	1	4

The optimal strategy is as follows:

$$\langle S[0], C_1, C_1, C_2, C_1, \ldots \rangle = \langle 1, 2; 1, 2; 1, 2; 3, 3, 1, 2, \ldots \rangle$$

where $S[0] = \langle 1, 2 \rangle$. The search process rapidly converges and stops after three steps demanding 23 hours: probability that the process does not stops at step 1 is 1; that it does not stop at step 2 is 0.4687, at step 3 is 0.1668, at step 4 is 0.0111, and at step 5 is zero.

6 Conclusion

In this work, we present a fast algorithm to solve the two-stage detection-and-rescue planning problem. In order to optimize the scheduling process, we use a greedy strategy, an index-based strategy, which is proven to be optimal when the objective is to maximize the lifesaving efficiency. The "best cluster" is selected at each stage, and the process is proved to be rapidly converging. Our solution is both simple and computationally efficient. When the confidence level is pre-defined, such local search strategies guarantees an optimal (max-efficiency) search sequences. In addition, using the suggested greedy methods can be applied to other search scenarios (e.g., with moving targets, agents-with-memory, etc.) and combining it with dynamic programming and biology-motivated heuristics can be a perspective direction for solving more complicated detection-and-rescue planning problems.

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