An Extended Time Horizon Search Technique for Cooperative Unmanned Vehicles to Locate Mobile RF Targets

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ABSTRACT

In this paper, we present a behavior-based, distributed, cooperative search algorithm for multiple unmanned aerial vehicles (UAVs) to cooperatively find sub-optimal search patterns to detect moving radio frequency (RF) signal emitting targets. The overall goal of the search algorithm is to compute sub-optimal flight trajectories for participating UAVs to minimize the combined search cost: search coverage, time, fuel usage, and communication overhead. The focus for this paper is to extend our existing search algorithm's ability to incorporate evaluations of flight path options beyond the immediate time horizon. The paper explores the trade-offs over the additional computation cost and the reduction of the total search time. In addition to finding a set of sub-optimal UAV search paths, the search algorithm also generates a priority list of possible search paths. The list is then used by an individual UAV to adjust its path selection to minimize a global search cost. Collectively, the selected UAV paths produce sub-optimal search patterns for a group of UAVs. The validity of the search algorithm is demonstrated using computer simulation.

KEYWORDS: cooperative search, distributed control, extension of time horizon

1. INTRODUCTION

Generating an optimal search pattern for any moving platform to find a target in a search area without any *a priori* knowledge of the search space and the target is a difficult problem. Such problem is often encountered by search and rescue teams when a missing person is reported in a forest area, pilots when a target must be detected visually in an open sea, or by UAVs when a set of mobile radio frequency (RF) emitters must be located.

It is well known that the traveling salesman's problem is an NP-complete problem. The search problems above fall under the same category of problems, making the cost to find the solution combinatorially untractable as the search space grows. The general consensus on the solution of such problem is that the computation cost grows exponentially as one seeks to find an optimal solution. The goal of any research in finding the solution to the current search problem should then be one of decreasing the rate of the exponential growth in computational burden as the search space increases. Such efforts bear fruits if one can model the search space or the target behavior in time. If no *a priori* information on the environment or the target is available, does it make sense to consider beyond the immediate present search points to minimize a search cost? In this paper, we address this problem in the context of multiple UAVs searching for mobile RF targets and provide some preliminary experimental results that show it is indeed beneficial to extend the time horizon. Theoretical work to support our experimental findings is under way.

The paper is organized as follows. Section 2 describes the scenario we use to solve the search problem. In section 3, we briefly present a distributed state-machine based control architecture we successfully developed using a set of behavior-based rules for cooperative UAVs[1]. The next section presents the time horizon extension search strategy followed by the result section. A few concluding remarks completes the paper.

2. PROBLEM DESCRIPTION

Figure 1 depicts the problem we are interested to solve. Given n UAVs and m mobile RF targets in a search space, find optimal paths for n UAVs to detect and localize all targets while minimizing an overall search cost. A UAV has a minimum and a maximum speed it can fly; the target also can move within a range of speed. The maximum speed of a target, however, is considered to be less than the maxi-

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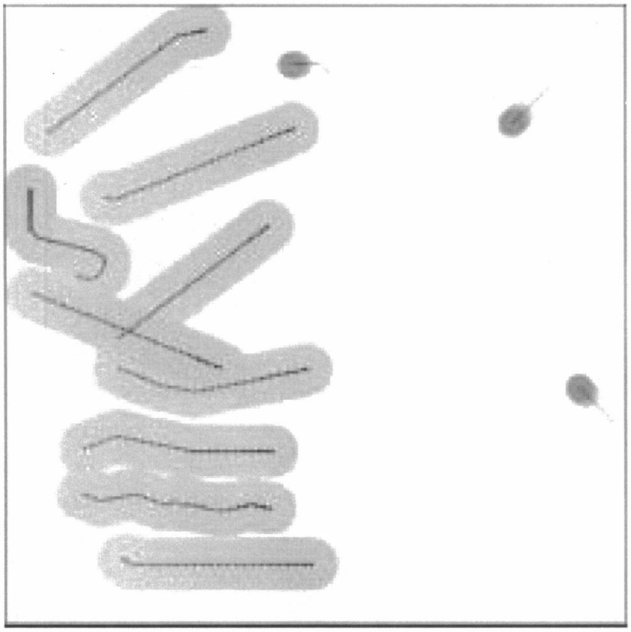

Figure 1: A snap shot of the graphical simulator: nine UAVs are searching for three targets in the space of 75 km by 75 km.

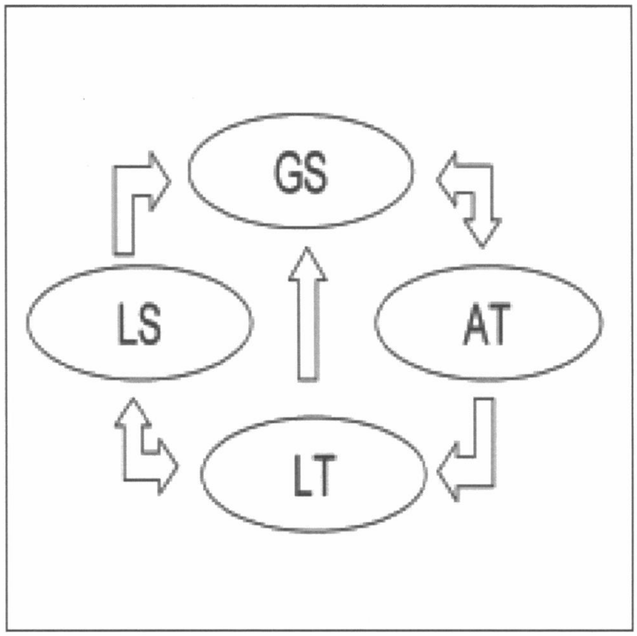

Figure 2: The state diagram governs the behavior of each UAV. This figure shows the transition paths between the GS, AT, LT, and LS states for a single UAV.

mum speed of a UAV. A target also has an option to stay stationary.

Each UAV is equipped with only a directional sensor and a global positioning sensor. When a target is detected, the directional sensor only provides the relative angle information of the target with respect to a UAV. No range information is available. This assumption means a single UAV can detect a target only after a considerable time and efforts: it must take multiple readings of a target as it flys around the target and must take into account of the movement of the target to estimate the target location. Furthermore we assume that the onboard directional sensor is inexpensive and can only provide the angle information within the accuracy of ± 7 degrees. That is, when a directional reading is taken, the actual relative angle of the UAV from the target can be off by as much as ± 7 degrees. Thus, multiple UAVs working cooperatively will reduce the time to locate an already detected target and will increase the accuracy of the target localization. We assume all UAVs have the same sensing capabilities and limited communication range. We also assume that the UAVs continually broadcast to neighboring UAVs their current positions, their next planned waypoints, and the angle to any detected target.

Our targets are mobile RF emitters. Each target uses a random number generator to determine how long it will emit signals and how long it will go silent. In addition, each target uses another random number generator to determine its movements in the search space. To make the problem even more challenging, UAVs have no pre-stored information or knowledge of targets and their movements.

Figure 1 shows a snap shot of our graphical simulator searching for mobile targets with nine UAVs and three targets. The larger circles represent paths of UAVs as they search over the search area. The dots in the middle of the circles represent the actual UAV positions and the radius of the circle is the maximum range for the onboard directional sensors to detect a target. Correspondingly, the smaller circles represent mobile RF signal emitting targets, the center dots show the positions of the targets, and the radius of the circles indicates the minimum distance a UAV must fly from a target to accurately localize the target. Note that the history of target locations are also displayed.

3. DISTRIBUTED CONTROL ARCHITECTURE

The control architecture is developed for multiple UAVs equipped with only crude directional sensors and global positioning sensors to search, detect, and localize mobile ground targets. Each UAV operates as a behavior-based state machine. There are four states in which a UAV can operate: (1) global search for targets (GS), (2) approach detected target (AT), (3) locate target (LT), and (4) local search for lost target (LS). When the movements of a set of individual decision making UAVs are combined together, they collectively complete the overall desired task of detecting and localizing all targets. We next present each stage briefly. For a full description, see [3]. Figure 2 shows the state diagram of the control architecture for a single UAV.

3.1 State One: Global Search (GS)

All UAVs start with this state. The movements of a UAV in this state is governed by a set of rules [2] to minimize a search cost function such as flying away from other UAVs and maintaining the direction of flying if possible. The collective search pattern is determined by combining cooperative and sometimes competing movements of each UAV. The global search cost is computed by adding the search cost for each UAV. The search cost for one UAV is shown below.

$$search\_cost = H\left(\frac{1}{\sum D_i} + \frac{1}{\sum D_j}\right)\left(\sqrt{\frac{|\phi|}{\pi/p}} + 1\right) \quad (1)$$

where H represents a numerical value indicating the explored history of a location. Since our targets can go silent at a time a UAV flys over, UAVs must keep track of the history of the search space to enable them to revisit previously explored areas. $\sum D_i$ and $\sum D_j$ represent the sum of the distances from known UAVs and the search area boundaries, respectively. We want our UAVs to move away from the boundaries of the search space to maximally explore the search area. The boundaries are arbitrary lines we can assign. To avoid missing mobile targets near the boundaries, we can simply expand the boundary lines to cover the original search area. Symbol ϕ is the turn angle required in radians, and p represents the number of discrete points examined to determine a turning angle.

3.2 State Two: Approach Detected Target (AT)

For cooperative localization of targets to occur, each UAV must have some mechanisms to decide whether or not it should respond to a communicated message informing that a neighboring UAV has detected a target. When such a message is received, a UAV uses the following equation to determine whether to participate in localizing the detected target or to continue in searching other yet to be detected targets.

$$cost = w_1 \frac{D}{D_{nomalized}} - w_2(n-s) + w_3(m-p) \quad (2)$$

Symbols D, $D_{nomalized}$,and n represent the estimated Euclidean distance from the current UAV location to the newly detected target, a normalized distance reflecting the size of the entire search area, and the required number of UAVs to accurately locate a target, respectively. Symbol s, m, and p denote the number of UAVs currently engaged in states LT or LS for the specified target, the total estimated number of targets in the search space, and the number of targets that have been detected or located, respectively. Finally, symbols w_i are the weights that can be used to influence the behavior of a UAV. With the exceptions of w_i and $D_{nomalized}$ all other variables are updated continuously as a UAV traverses in the search space.

3.3 State Three: Locate a Target (LT)

When a UAV reaches the estimated target localization orbit (shown as the smaller circles in Figure 1) the state automatically changes from AT to LT. Once a UAV enters the orbit, it coordinates its flying speed with other UAVs on the orbit to fly in an equi-angle apart formation. The task is performed by intentionally communication among UAVs who are operating in the LT state to localize a target. As a result of a trade-off study, our current implementation limits the number of UAVs participating in localization of a target to three, making the final formation to cause UAVs to be 120 degrees apart from each other on the target localization orbit. The actual localization is done using either the triangulation technique or the Kalman filtering technique[4].

3.4 State Four: Local Search for Lost Mobile Target (LS)

A UAV enters the fourth state only when an emitter stops transmitting signals while a localization process is taking place but has not been completed. When such situations occur, UAVs that are currently involved in localizing the target switch from the LT state to this state. The UAVs gradually increase the radius of the localization orbit over time. The rate of increase is a function of time and the two past observations of the target locations guide the center of the enlarged orbit. The equation that governs the target localization orbit is as follows.

$$\{x - [e_x(t-1) + c_x(e_x(t-1) - e_x(t-2))]\}^2 +$$

$$\{y - [e_y(t-1) + c_y(_y(t-1) - e_y(t-2))]\}^2 = (r(t) + kt)^2$$

where $e_x(t-1)$ and $e_y(t-1)$ are the last seen x and y locations of the emitter; $e_x(t-2)$ and $e_y(t-2)$ are the second last seen x and y locations of the emitter; $r(t)$ represents the radius of the current orbit; c_x and c_y are constants chosen to weigh the movement of the emitter location based on the past history; and kt represents the increase in the localization orbit radius based on the elapsed time (t) and constant (k) to accommodate the movement of the emitter location. When an emitter signal is detected, the localization orbit equation reduces to the following.

$$[x - (e_x(t))]^2 + [y - (e_y(t))]^2 = r(t)^2$$

Figure 3 shows a sequence of snapshots showing the entire process of UAVs searching, detecting, and localizing RF mobile targets.

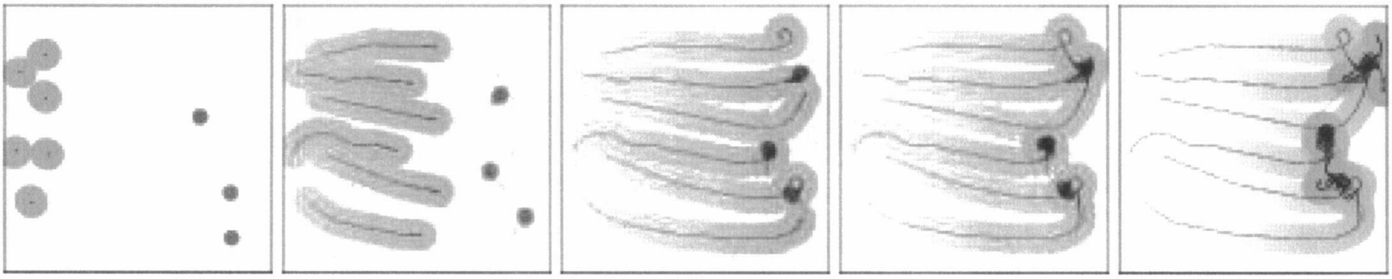

Figure 3: Snapshots showing the process of searching, detecting, localizing three mobile targets using six UAVs. Frame (a) shows the initial locations of UAVs (larger circles) and targets (smaller circles). Frame (b) shows the search pattern generated when all UAVs are operating in the GS state. Frame(c) shows a target detected by a UAV, which starts orbiting the emitter and transmits its discovery of a target to nearby UAVs. In frame (d) shows that two other nearby UAVs have responded to the call and orbiting the target to localize the targets. Finally, frame (e) shows that the targets have been fully localized, represented by a square

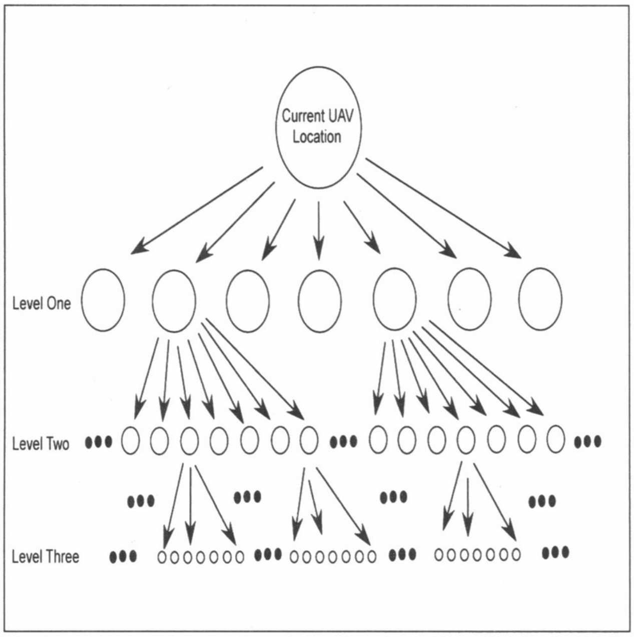

Figure 4: Each UAV continuously evaluates the search cost as it determines the next waypoints.

4. EXTENDING TIME HORIZON SEARCH TECHNIQUE

During the global search state, each UAV seeks to find waypoints to minimize the search cost function. The next waypoint is determined by evaluating the cost function values for seven discrete search points ahead of the UAV as shown in Figure 4. The process of evaluating the cost function takes place once every twelve seconds, which allows each UAV to modify its search pattern continuously.

Our search technique extends the evaluation of waypoints up to three future time levels; future waypoints are generated by extending each immediate seven waypoints to branch off to include the next level waypoints. The process is illustrated in Figure 5. Frame (a) shows one UAV evaluating seven discrete points for the next immediate time horizon, frame (b) shows a UAV considering next two levels of waypoints, and frame (c) shows a UAV evaluating for the next three levels of waypoints. The arrows indicate the sub-optimum path selected, returning the minimum cost from equation (1).

It is obvious that this process can not continue without combinatorial explosion to take place. To reduce the computational complexity, UAVs use the greedy search technique to prune the search paths before they explore the next level of possible waypoints. It is important to note that as each point in the 'search tree' is evaluated, a UAV incorporates the future waypoints broadcasted by the neighboring UAVs in making its decision.

5. RESULTS

In this section we present quantitative results on the total time required to search, detect, and localize all targets in a search area as we vary the number of waypoint levels in the time horizon considered by a UAV. All our simulation results are performed in a 75 km x 50 km area.

The first experiment was conducted with six UAVs and six mobile RF targets. The initial locations of the six UAVs and six targets are randomly generated; 100 runs were performed and their results are averaged. For the experiment, seven degree directional sensors are used. The maximum sensor range was 4.3 km, the maximum communication range was 40 km, and the UAVs tried to fly an orbit of 2.2 km from the estimated target location for localization. The

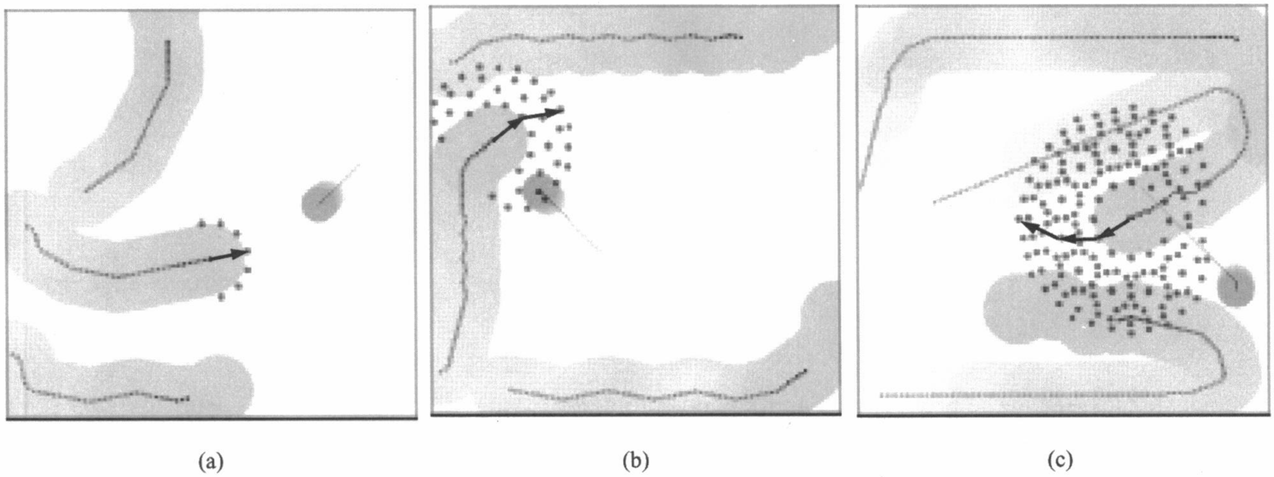

Figure 5: The figure shows how the current UAV location generates possible waypoints as the UAV looks beyond the immediate time horizon at level one (frame (a)), level two (frame (b)), and level three (frame (c)).

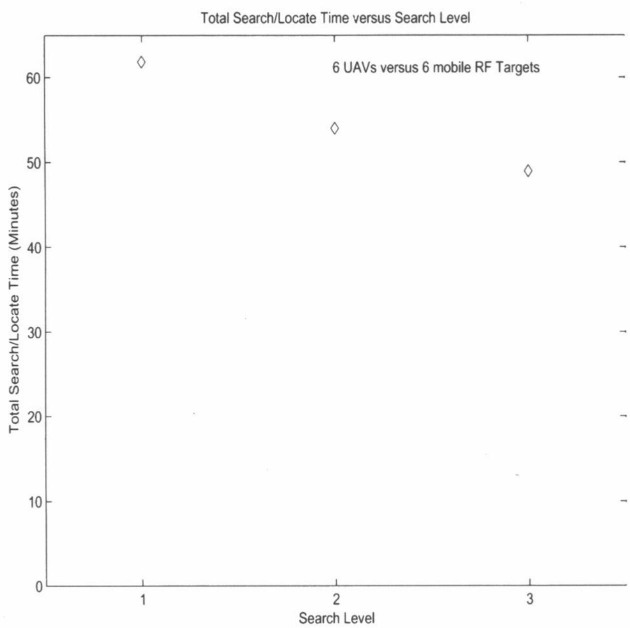

Figure 6: Plot of the total time required to search, detect, and localize six targets using six UAVs as we extend the time horizon.

velocity for a UAV varied from 115 kph to 260 kph while the target velocity ranged from 0 kph to 37.5 kph. The final localization estimate for a specific target was delayed until the target stopped emitting, giving the UAVs the maximum time possible to get in the proper geometry.

Figure 6 shows the total time required to complete the task of searching, detecting, and localizing all six targets using six UAVs as the number of levels to extend the time horizon is varied from one to three.

The experiment clearly shows that as the UAVs look ahead beyond the immediate time horizon, the total search time decreases, indicating that it pays off to 'look' ahead even if UAVs do not have any *a priori* knowledge or information of the search space and targets.

In our next experiment, we measured the time to search, detect, and localize nine mobile RF targets using six UAVs. We recorded the time it takes for the UAVs to detect one through nine mobile targets to evaluate the search performance as we extend the time horizon. Figure 7 shows how the search time changes as each UAV computes for the next waypoint using one, two, and three search levels. As can be seen, the results did not vary much in detecting the first target, but the time to get all nine targets is significantly different as the number of time levels included for planning changes. Each case was run 100 times and their average values are recorded. Again, this preliminary experiment shows that if we can afford the computation cost of finding the sub-optimal UAV paths, the overall search time can be reduced. Currently, a type of greedy search technique to extend the time horizon is used. We plan to conduct theoretical study to compare a variety of techniques to decrease the computational complexities involved in generating UAV trajectories.

6. CONCLUSION AND FUTURE WORK

In this paper we studied the effect of extending the time horizon to select sub-optimal flying waypoints of a UAV in the context of multiple UAVs cooperatively searching, detecting, and locating ground based RF mobile targets. We showed that when waypoints of cooperative UAVs are selected by considering the future waypoints of UAVs, the waypoints of UAVs collectively reduce the overall search time for detecting mobile RF targets. The results show that

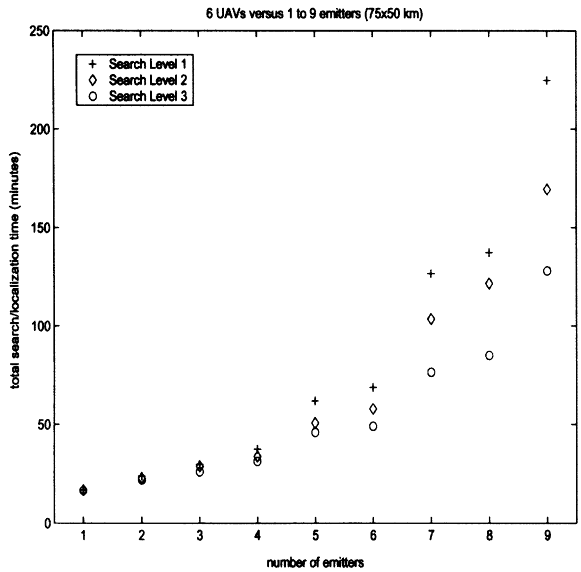

Figure 7: This figure shows the required time to detect nine targets using six UAVs. The y-axis shows the average search time in minutes and the x-axis shows the number of targets detected.

the extension of time horizon technique enhances the overall search task even if UAVs have no *a priori* information of the environment and the mobile targets, except the size of the search area.

We demonstrated our proposed approach using simulated results. We plan to study methods to further decrease the search time by increasing the number of levels included to generate sub-optimal search paths while keeping the computational burden at minimum. We also plan to implement the experiment using hardware UAV platforms.

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