Parametric Control of Multiple Unmanned Air Vehicles over an Unknown Hostile Territory

K. Madhava Krishna*+ Henry Hexmoor*~ Subbarao Pasupuleti* James Llinas~
* CSCE Dept. University of Arkansas, Fayetteville AR 72701
+ Indian Institute of Information Technology, Hyderabad, India
~ Center for Multi Source Information Fusion, SUNY Buffalo
mkrishna@uark.edu hexmoor@uark.edu spasupu@uark.edu llinas@eng.buffalo.edu

Abstract— *A methodology for real-time control of unmanned air vehicles (UAV) in the absence of a-priori knowledge of hostile territory is presented. The control methodology generates a sequence of waypoints to be pursued by the UV until the goal is reached. The controller computes the waypoints every time new information is obtained regarding the presence or absence of a hostile agent at a particular grid of the territory. The waypoints are the result of an A* search. The cost function of the search is a weighted combination of dangers arising due to probability of being hit by the attacks of hostile terrestrial agents on the ground and the danger of UAV grounded as a result of its prolonged stay over the hostile territory. The multi-agency in the system is due to the broadcast of newly observed information by an UAV to its remaining counterparts. The sequence of waypoints defines the path of the UAV to its goal. By varying the corresponding weights the paths can be altered to obtain a particular performance criterion. Simulation results are presented for various parametric combinations to validate the methodology.*

1. INTRODUCTION

Cooperative control of multiple UAVs has broadly focused on the areas of flight formation, cooperative path planning such as for a rendezvous and resource allocation in the form of target assignment much akin to the main themes of research in multi robotic agents. The main motivation in UAV formation has been in increasing stealth and improving fuel resources. The essential theme here has been to couple UAVs based on their aerodynamic interactions such that the entire formation is considered as a holistic system for which the control law is generated [1,2,3 of McLain's].

Path planning and resource allocation problems consider UAV as independent of one another. In path planning one of the main focus has been in sequencing of UAVs for arrival at specified locations or targets such as the rendezvous [4=> 9 in McLain] and target intercept problems [5=>downloaded McLain].

Resource allocation methods have concentrated upon target assignment [6,7=>5,6 pf McLain] and classification [8=>7]. In [7] a scheme based on hierarchical decomposition is presented to allocate a sub-team of UAVs to a particular task. In [5] the authors present an algorithm such that the UAVs reach the target at the same instant of time by avoiding pop up threats whose locations are known a-priori. A coordinated search is made through a vornoi diagram.

This paper presents a strategy that is a variant of [5] in that the UAVs can be coordinated to arrive at a desired target location or respective target locations within a specified temporal upper bound. However unlike [5] the locations of the targets are not known a-priori. The waypoints are generated through an A* search and the search is repeated every time an UAV agent discovers new information.

The rest of the paper is organized as follows. Section 2 describes the modeling of the hostile habitat in the form of grids with probability values. Section 3 discusses the A* search as an optimization of a cost function that combines the instantaneous danger of being fired while passing over a grid and the danger due to cumulative fatigue accrued by the UAV over its sojourn above the hostile territory. Section 4 presents the simulation results and analysis while section 5 concludes the paper along with the further scope of this work.

It is worthwhile to note that research in multi robotic systems, which has a longer history has been along similar lines of formation control [9,10], resource allocation schemes such as in target observation and tracking [11,12] as well as cooperative planning and reactive navigation methods [13,14]. It is beyond the scope of the paper to compare the approaches in the robotic community vis-à-vis the ones used by the UAV researchers from the point of view of motivation, implementation and the methodology of approach.

2. HABITAT MODELING

The hostile zone is divided into a number of square cells. The firing strength, fs_j of the hostile agent, HA, occupying cell j represents the probability that it can shoot down a UAV when the UAV flies over the cell occupied by it. The probability of shooting down a UAV decreases when the UAV flies over the cells adjacent to that occupied. In an eight connected sense, the four nearest neighbors are denoted as N1and the four diagonal neighbors by N2. If the distance between centers of two four connected cells is termed a unit, cells that are two units away are also denoted as N2. The labeling of cells with respect to an occupied cell, O, is shown in figure 1.

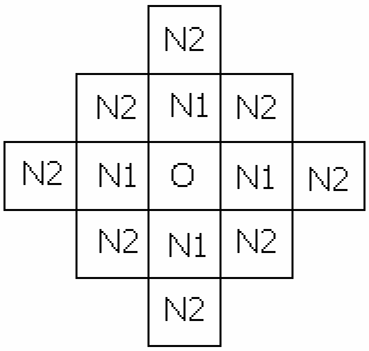

Figure 1: Labeling of cells with respect to O, the cell that is occupied by a hostile agent

For an UAV that flies over a cell i the probability that it gets shot by a HA is given by

$$p_{s,i} = \begin{cases} fs_O; i \in O \\ fs_{N1}; i \in N1 \\ fs_{N2}; i \in N2 \\ 0; elsewhere \end{cases} \quad fs_O < fs_{N1} < fs_{N2} \qquad (1)$$

In other words if the UAV flies directly over the occupied cell it has the maximum probability of getting hit and its probability decreases as it flies over N1 and further decreases over N2. Equivalently p_{si} is also the probability that a HA situated at a cell j fires successfully at the UAV over i and is denoted by p_{fj}. Hence $p_{si} = p_{fj}$.

Thus for an UAV over i the cumulative probability of being shot is the union of the individual probabilities of being successfully fired by HAs positioned at the cell beneath or any of the N1 or N2 cells. If the cumulative probability of being shot is given by P_{si}, then

$$P_{si} = \bigcup_j p_{fj}, \; j \in O \; or \; j \in N1 \; or \; j \in N2 . \qquad (2)$$

In the absence of a-priori information regarding the occupancy of the cells in the habitat, the prior probability of a cell j being occupied by a HA is denoted by p_{Oj}. The cumulative probability of being shot when flying over cell i under lack of such information is then given by

$$P_{si} = \bigcup_j p_{Oj}.p_{fj}, \; j \in O \; or \; j \in N1 \; or \; j \in N2 . \qquad (3)$$

It is assumed that the apriori knowledge regarding the number of HAs, n_{HA}, is known while their coordinates or the cells that they occupy are unknown. In such a case if the total number of cells is n_C, then $p_{Oj} = \frac{n_{HA}}{n_C}$. As the UAVs move over the habitat they obtain information regarding the occupancy or non-occupancy of a cell that is broadcasted to the other UAVs. The occupancy probabilities of cells for which there is no information yet is recomputed as

$$p_{Oj} = \frac{n_{HA} - n_V}{n_C - v} \qquad (4).$$

In (4) n_V represents the number of cells found occupied by HAs among the v number of cells for which information was sensed and broadcasted by the UAVs.

3 COMPUTING UAV PATHS

An A* algorithm is used to compute UAV paths till the target. The nodes are the cells and the edges are the links that connect a cell to its eight neighbors. For an edge directed from cell m to cell n the cost of traversing the edge C_{mn} is given by the weighted combination:

$$C_{mn} = (1-w) y d_{mn} + w P_{sn} \qquad (5)$$

In (5) P_{sn} is same as the left hand side of equation (3), the cumulative probability of being shot at cell n. The distance between the cells in an Euclidean sense is given by d_{mn}, while yd_{mn} represents the fatigue accrued by the UAV for traveling a distance d_{mn}. y is a normalization constant that allows d_{mn} to be scaled to similar values as P_{sn}. And w is the weighing factor that takes values in [0, 1] and decides the proportion of priority or importance to either of the two costs involved. Essentially (5) suggests the cost of traveling from cell m to cell n is due to the overall probability of being fired at cell n as well as the fatigue developed with distance. We also denote this fatigue as distance anxiety or the anxiety that results as the UAV covers more distance and hence spends more time within the hostile habitat.

Paths are recomputed whenever information regarding a new cell in the form of presence or absence of a HA occupying it is obtained. The occupancy probabilities of unobserved cells are recomputed through (4) and the cost matrix updated using (5) that is made use of to recomputed new paths.

3.1 Search within a temporal upper bound

The UAV's search can be controlled such that they reach a given target location within a specified temporal upper bound. This is done by a search in the space of w. For instance $w = 0$ corresponds to the search that outputs paths of least distance and hence least possible time paths under

assumption of constant velocity. Similarly $w=1$ results in paths of least probabilistic resistance that need not be optimal in terms of distance.
It is to be noted however that increasing w does not always imply increasing path lengths – it only implies paths with reduced chances of being fired or a search that is biased towards least probabilistic paths. Similarly decreasing w does not always imply paths with increased chances of getting fired – it only implies a search that is biased towards shortest distance paths. In other words a path of least probabilistic resistance obtained for $w=1$ could well be a path that is shortest in terms of distance metric as well and vice versa.

The temporal upper bound is specified in terms of the base value that corresponds to the shortest possible time to reach the target. For example an upper bound of 1.2 entails that the UAV reach its target within 1.2 times of the shortest possible time. Thus for a given upper bound time a search is made by decreasing w from 1 to 0. All paths for a UAV that satisfies the upper bound are stored. Among those the path that corresponds to shortest probabilistic resistance or shortest distance is chosen according to the criterion specified or appropriate.

The overall algorithm for a given time upper bound is delineated below.

THE ALGORITHM

1. For all UAVs alive in the system do steps 2 to 3 until the last waypoint or target is reached.
2. If new information is obtained in the form of presence or absence of a HA at a cell either through observation or broadcast do steps 2a till 2d
   2a. Update occupancy probabilities at the cells
   2b. Compute the new cost matrix based on the recent probabilities.
   2c. Search in the space of w for all paths that satisfy the time upper bound
   2d. Among those paths that satisfy the upper bound select the path that is least in terms of probabilistic resistance or distance metric
3. Move towards the next waypoint

4 SIMULATION RESULTS

The figures 2a, 2b and 2c show the paths of UAVs for $w=1, 0.5 \& 0$ respectively. The occupied cells are labeled as O, and the N1, N2 neighbors are identified with respect to them as shown in figure 1. However the UAVs themselves are not aware of their locations a-priori until one of them identifies the HA during flight. An UAV's sensing range at any instant is defined as the area covered by 9 cells, three along the length and three along the breadth. In color the cells that are occupied are shown in *red*, their N1 neighbors by *magenta*, N2 neighbors by *yellow* and those that are neither occupied nor N1, N2 neighbors by *gray*. If viewed in grayscale the O cells appear darkest, N1 cells are moderately dark but both N2 neighbors and those that are neither O nor N1 appear white. In figure 2a alone the N1 and N2 cells are also labeled. For other figures only the O cells are shown labeled but the N1 and N2 cells are the same as in figure 2a, for the section discusses results pertaining to this environment alone.

As expected, despite lack of a-priori knowledge of the locations of HAs, for $w=1$, the UAVs managed to find their paths through the cells where the probability of getting fired is minimum, such as the N2 cells and the unclassified cells. On the contrary for $w=0$ the UAVs move through the O cells to minimize their distance. It is to be recalled that the shortest distance is not a straight line between start and target locations since the graph search is through an eight connected lattice. For $w=0.5$, the paths turn out to be neither shortest distance paths or shortest probability paths but paths that minimize $C_{mn}=0.5(yd_{mn}+P_{sn})$.

Table 1 tabulates the analysis for the figures 2a – 2c. The first column denotes w for the three runs, namely, $w=1, 0.5 \& 0$. The second column signifies the sum of the prior probabilities averaged for the paths of the ten UAVs in the system. The prior probabilities are the probability of getting fired at a particular cell as believed by the UAV when partial knowledge of the habitat was obtained. This corresponds to a situation where 15% to 25% of the locations of the HAs were identified. The third column shows the sum of the posterior probabilities computed along each path of the UAV averaged over the UAVs. This is computed at the end of the simulation based on whatever knowledge of the environment that had been finally gathered and disseminated among the UAVs. This knowledge does not encompass the complete knowledge of the system but the best possible knowledge obtained over a simulation. This would be the complete knowledge had all the occupied locations were visited by the UAVs. The fourth column denotes the average distance traversed by the UAVs in a simulation and the final column depicts the time bound within which the UAVs manage to reach the target. In these simulations the UAVs are not shot down and hence manage to reach the target, however the nature of the paths taken is analyzed based on the probability of getting fired and the distance traversed.

The sum of probabilities can exceed 1 since it merely adds up the chances of being fired at each of the cell visited and that will be visited in future by the UAV based on the path computed at that instant. While it is this sum that gets minimized during the A* search for paths of least probability this is different from the computation that evaluates the probability that an UAV gets past l cells safely. For that computation is given by $\prod_{i=1}^{l}(1-P_{si})$ and is called the safety factor of a path that traverses l cells. However it can be shown that at any given instant based on the knowledge of the environment at that instant the path that minimizes the sum of probabilities would also be the one that gives the maximum value of safety factor. And this would be done elsewhere.

It is seen that for w = 0 the paths with least prior and posterior probability sums but with maximum distances are obtained. This is due to the fact that the paths of least probabilities are through the center of the environment and the UAVs that enter the habitat at the top and bottom search their way to the center due to lack of prior information about the HAs' locations. It is also seen that for w=1 the paths obtained are shortest in distance and hence the fatigue accrued due to it but also highest in chances of being fired. Though paths of shortest distance need not be the paths of highest chances of being fired it so happens for this environment that such paths coincide with areas of highest probability of being fired. It can be seen that the UAVs at the top and bottom move through a continuous array of occupied cells since that path is the path of least distance fatigue or distance anxiety. For w=0.5 the probabilities as well as distances are in between those obtained for w=1 and w=0.

In figure 3 the path that would have actually resulted if the information gathered during the entire course of the simulation of figure 2a was made available at the start. In such a case the path of UAVs in figure 3 are still through the center of the habitat as in 2a with some variations but with distances reduced. The distances are reduced for the UAVs that enter the habitat from the top and bottom since they do not search for the area of least probability of being fired but directly head towards it in an eight connected motion.

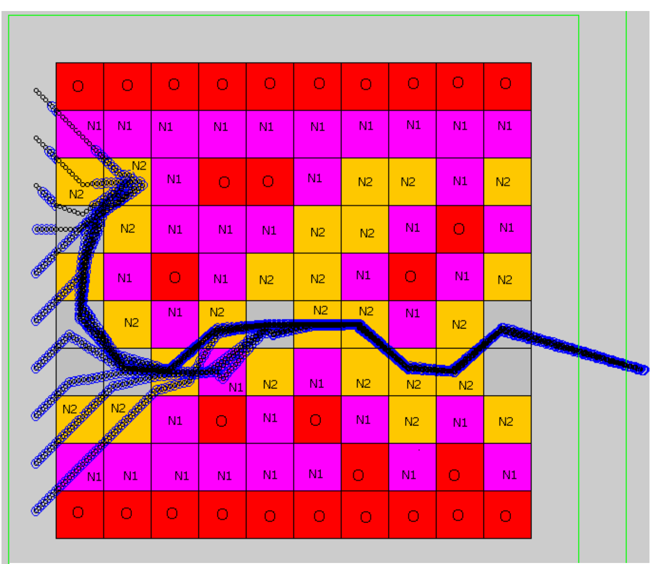

Figure 2a: The paths traced by the UAVs for w=1. The cells are labeled as O, N1 and N2

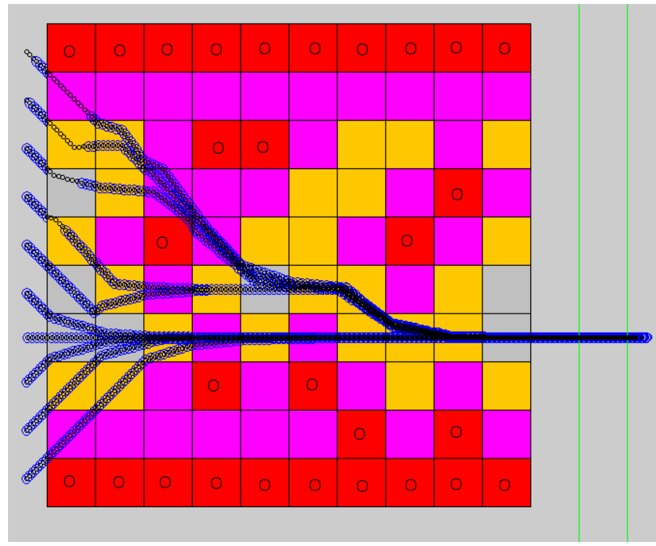

Figure 2b: The paths traced by the UAVs for w=0.5. Only the O cells are shown labeled

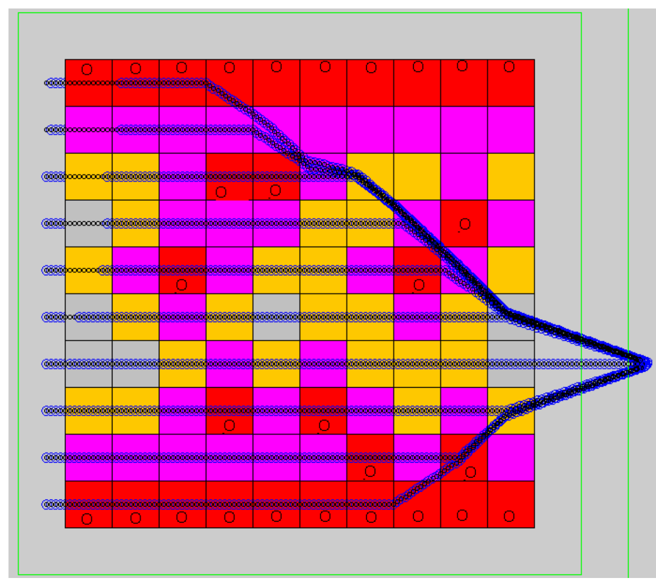

Figure 2c: The paths traced by the UAVs for w=0.

w	Prior Probability sum	Posterior Probability sum	Distance traversed	Upper bound on time
1	0.41	0.46	6973	1.4
0.5	0.45	0.58	6541	1.3
0	0.54	1.27	5450	1

Table 2: Analysis for the figures of 2a, 2b and 2c with their corresponding weights, w = 1, 0.5 and 0. The probabilities and distances are averaged over the 10 UAVs present in the system

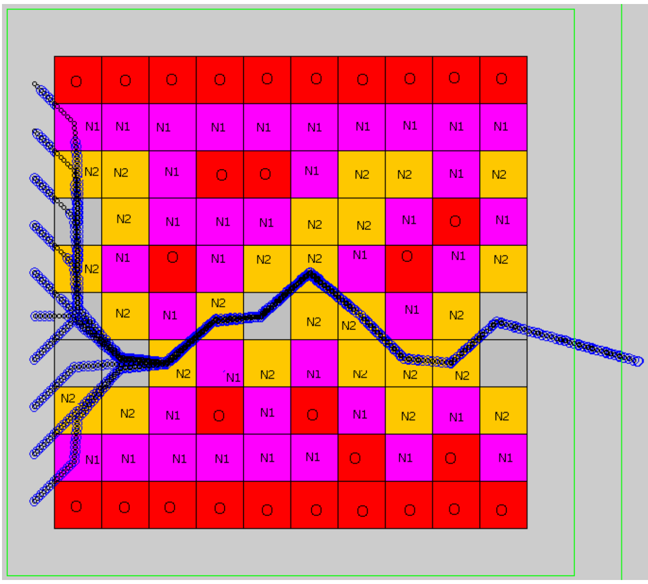

Figure 3: Paths obtained for w=1, when the information gathered at the end of simulation in figure 2a is made available to the UAVs at the start.

5 CONCLUSIONS AND SCOPE

A methodology for parametric control of multiple UAVs is presented such that a desired criterion is met. The desired criterion can be a upper bound on time to reach the target or one that minimizes distance fatigue or the path that minimizes the chances of being fired. The method works for situations where a-priori knowledge of the hostile habitat is unknown. It also lends itself to situations where the trajectories of UAVs can be modified on the fly by modifying the weighing factor, w, since the paths are recomputed every time a new information about the location of HA is obtained. Future scope of this work includes incorporating communication constraints such as latency, minimum distance to be maintained between UAVs for information exchange and an investigation into the role for embedding the UAV agents with social notions like autonomy and benevolence that yielded useful results in [14,15].

ACKNOWLEDGEMENTS

This work is supported by CUBRC subcontract number 6665-2 issued by Dr. James Llinas to the university of Arkansas CSCE dept.

REFERENCES

[1] F Giuletti, L Pollini and M Innocenti, "Autonomous formation flight", *IEEE Control Systems Magazine*, 20: 45-52, Dec 2000

[2] C Schumacher, "Nonlinear control of multiple UAVs in formation flight", *Proc. of AIAA GN&C Conf.*, Aug 2000

[3] S Singh, M Pachter, P Chandler, S Banda, S Ramussen and C Schumacher, "Input output invertibility and sliding mode control for close formation flying", *Proc. of AIAA GN&C Conf.*, Aug 2000

[4] T McLain, P Chandler, S Ramussen and M Pachter, "Cooperative control of UAV rendezvous", *Proc of the ACC*, pp. 2309-2314, June 2001

[5] T McLain, R Beard and J Kelsey, "Experimental demonstration of multiple robot cooperative target intercept", *AIAA Guidance and Control Conference and Exhibit*, Aug 2002, Monterey, CA.

[6] R. Beard, T. McLain, M. Goodrich, and E. Anderson, "Coordinated target assignment and intercept for unmanned air vehicles," *IEEE Transactions on Robotics and Automation*, 2002.

[7] K. Nygard, P. Chandler, and M. Pachter, "Dynamic network optimization models for air vehicle resource allocation," in *Proc. of the ACC*, pp. 1853–1856, June 2001.

[8] P. Chandler, M. Pachter, K. Nygard, and D. Swaroop, *Cooperative Control and Optimization*, ch. Distributed Cooperation and Control for Autonomous Air Vehicles. Kluwer, 2001.

[9] T. Balch and R. C. Arkin. Behavior-based formation control for multirobot teams. IEEE Transactions on Robotics and Automation, 14(6), December 1998.

[10] A. K. Das, R. Fierro, V. Kumar, J. P. Ostrowski, "A vision-based formation control framework, *IEEE Trans. Robot. And Automat.*, vol. 18, no. 5, pp. 813- 825, 2002.

[11] Maja Matric, Gaurav Sukhatme and Esben Ostergaard, "Multi-robot Task Allocation in Uncertain Environments", *Autonomous Robots* 14, 255-263, 2003

[12] S. Botelho and R. Alami., " M+: a scheme for multi-robot cooperation through negotiated task allocation and achievement." *In Proceedings of the 1999 IEEE/RJS International Conference on Intelligent Robots and Systems*, 1234-1239, 1999.

[13] M. Bennewitz, M., W. Burgard and S. Thrun, "Finding and Optimizing Solvable Priority Schemes for Decoupled Path Planning Techniques for Teams of Mobile Robots", *Robotics and Autonomous Systems*, 41 (2), pp. 89-99, 2002.

[14] K Madhava Krishna, Henry Hexmoor and S Chellapa, "Reactive Navigation of Multiple Moving Agents by Collaborative Resolution of Conflicts", *Journal of Robotic Systems*, in print.

[15] K. Madhava Krishna, Henry Hexmoor and P Subbarao, "Role of Autonomy in a Distributed Sensor Network for Surveillance", *Proc. of ICAI 2004, (Intl Conf. on Artificial Intelligence)*, Las Vegas, July 2004.