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Multi-step Look-Ahead Policy for Autonomous Cooperative Surveillance by UAVs in Hostile Environments

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***Abstract*— In this paper a real-time cooperative path decision algorithm for UAV surveillance is proposed. The surveillance mission involves multiple competing objectives. To handle these competing objectives, a layered decision framework is proposed, in which different objectives are deemed relevant at different decision layers depending on their priorities. Compared to previous work, in which multiple objectives are integrated into a single global objective function, this layered decision framework allows an objective with higher priority to be satisfied first by eliminating possible compromises from other less important ones. An important objective of the path decision algorithm is to navigate the UAV safely in a hostile environment. To achieve this, the key is to increase the time horizon of the path decisions. A multi-step look-ahead path decision strategy based on a Roll-out Policy is proposed. This policy has moderate complexity and, when used in the layered decision framework, it is able to find safe paths effectively and efficiently. For the guidance of a group of UAVs, the use of small path-decision groups and the assigning of different tasks to different UAVs can also be incorporated into the algorithm, which makes it more flexible in such scenarios.**

I. INTRODUCTION

Recently a considerable amount of research effort has been directed toward the navigation and cooperative control of groups of Unmanned (or uninhabited) Aerial Vehicles (UAVs) [14], [5], [6], [12], [8]. In this paper, we focus on the surveillance application of UAVs. Under a centralized information structure, the objective is to develop a real-time path decision algorithm for a group of UAVs to carry out multi-objective surveillance in a hostile environment. The objectives of the surveillance include: i) Navigate the UAVs safely in a hostile surveillance environment; ii) Search for new targets; iii) Classify the detected targets; and iv) Maintain tracks on the detected targets. In the previous work [16], these objectives were combined into a single global objective function. The path decision problem was formulated as a nonlinear programming problem and solved by optimizing the global objective function over the continuous control variables (turn rates of the UAVs). However, there are several drawbacks to this approach. First, since different objectives have different meanings, the weighted sum of the objective functions is difficult to interpret and validate. Secondly, the simultaneous impacts of multiple objectives on the path decisions could compromise the accomplishments of one on another objective in an unpredictable manner. As shown in Section IV, the survival probabilities of the UAVs can drop significantly when a combined global objective function is used for path decisions. Lastly, due to the complexity of this formulation, it was used to generate decisions with a one-step look-ahead approach only, i.e., a myopic policy.

In this paper, a Layered Decision Framework is proposed for the handling of the competing objectives and a multi-step look-ahead strategy using a Roll-out Policy are proposed for path decisions. Combined, they are shown to be able to solve the problem of safe navigation and guide the UAVs for multiple objectives in a hostile environment.

Two additional features can also be incorporated into the path decision algorithm, which make it more flexible to control a large number of UAVs. One is the formation of decision groups. Another is to assign different objectives to different UAVs. For conciseness, their details are in the full version of this paper [20].

Section II describes the surveillance problem. Section III is devoted to the layered decision framework for multi-objective surveillance. In Section IV, the multi-step look-ahead path decision strategy is proposed, and it is shown to be effective in solving the problem of safe navigation. Section V discusses issues when the algorithm is used to guide a group of UAVs. Section VI provides the conclusions.

II. THE SURVEILLANCE MODELS AND OBJECTIVES

Assume that fixed wing Unmanned Aerial Vehicles are used in a surveillance region. The UAVs can fly only within a speed interval and have limited maneuverability. Following the formulation in [16], it is assumed that the UAVs move with a constant speed $\mathrm{V_{uav}}$ and the maximum turn rate the UAVs can take is $\Omega_{\max}$. Unlike in [16], the control of the UAVs is discretized into D levels, namely the UAVs can only take turn rates from a finite set. For example, when $D = 3$ the control set is $\{-\Omega_{max},\, 0,\, \Omega_{max}\}$. It is assumed that the path decisions are made every T seconds. For cooperative surveillance, the UAVs need to exchange information of their states and measurements from the onboard sensors. In this paper, a centralized data processing framework is used, that is, all the information from the UAV network is available for data fusion and path decisions. While the proposed path decision algorithm works best in a centralized setting, it can

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be used in a distributed manner by treating each individual UAV as a duplication of the decision center. The issue of synchronizing information among distributed agents (UAVs) in a distributed system is beyond the scope of this paper.

Objectives of the surveillance include: “Safe navigation”, “Tracking”, “Search” and “Classification”. Details of their models and objective functions are presented in [19], which are similar to the formulations in [16]. This paper focuses on the use of these objective functions for the path decisions of the UAVs and here we only bring in those necessary definitions and notations.

For “Tracking”, the sate of the target is defined as $X = [x\ \dot{x}\ y\ \dot{y}]'$. At time kT the expected track (information) update for target j at time $(k+1)$T is

$$\hat{I}_j(k+1|k+1) = I_j(k+1|k) + \sum_{s=1}^{N}\{\hat{\pi}_D(s,j,k+1) \cdot \hat{H}(s,j,k+1)' \hat{R}(s,j,k+1)^{-1}\hat{H}(s,j,k+1)\} \quad (1)$$

where I_j denotes the information matrix which is the inverse of the covariance from the track: $I_j = P_j^{-1}$, $\hat{\pi}_D(s,j,k+1)$, $\hat{H}(s,j,k+1)$ and $\hat{R}(s,j,k+1)$ are the expected detection probability, observation matrix and measurement covariance matrix. To evaluate the expected quality of the track, the mean square position error (MSE) is used, since it is directly related to the RMS position (components 1 and 3 of the state vector) error. For target j the predicted MSE is

$$\widehat{MSE}(j,k+1) = \hat{P}_j(k+1|k+1)_{(1,1)} + \hat{P}_j(k+1|k+1)_{(3,3)} \quad (2)$$

For “Safe navigation”: survival probability of the UAVs is denoted as π_S, which is a vector. The sth element, $\pi_S(s)$, of π_S is the survival probability of UAV s. The vector $\hat{\pi}_S$ denotes the expected survival probability of UAVs.

For “Search”, the surveillance region is divided into $M \times N$ sectors, and $P_{m,n}$ denotes the probability that there is no new target in the sector; the target arrivals are modeled as a Poisson process.

For “Classification”, μ_j is the the class probability vector for target j, which contains the probabilities that target j belongs to each possible class.

III. Layered Decision Framework for Multi-objective Surveillance

In this paper, a layered decision framework is proposed to handle the multiple objectives in the surveillance, in which each objective occupies a decision layer according to its priority. A decision layer consists of: i) The objective; ii) A function that evaluates the degree of accomplishment of the objective; iii) A satisfactory level of the objective, at which point no further improvement is necessary. Table I shows an example of arrangement of the decision layers. In the layered decision framework, an objective with higher priority will be considered first. The key idea is once a satisfactory level is reached on an objective, the “satisfied” objective will have no effect on the path decisions; thus the remaining freedom in the path decisions can be passed on to the next decision layer. To illustrate this, consider a simple case of a group of $N = 2$ UAVs tracking two targets while performing search in the surveillance region. Suppose the control of each UAV is discretized into $D = 3$ levels. At every decision epoch, the number of control options for the UAV group is $D^N = 9$. For simplicity, the example will stay with one-step look-ahead path decision (a multi-step look-ahead strategy will be proposed later). All the data in this example are for the purposes of illustration only.[1]

In the layered decision framework, the control options are first evaluated in the top decision layer of “Safe navigation”. Table II shows the resulting m best control options ($m = 5$ in this case) marked with “$\surd$”. They form a reduced control set, which is passed on to the second decision layer of “Tracking” for further selection. Similar procedures as in Tables II are used in other decision layers, e.g., “Tracking” and “Search”, except that different evaluation functions and satisfactory levels are used. Sifting through the decision layers, the path decision algorithm ends when the best control option is found. The uniqueness of the final path decision can be guaranteed by simply setting the “satisfactory level” of the last decision layer to the “ideal” one. In this example, the last decision layer is “Search”, thus τ_{PNNT} can be set to 1, which is an “ideal” level that can never be attained.

Compared to the weighted sum approach, the layered decision framework has the following advantages:

- Multiple objectives of surveillance are clearly delineated. Objectives with higher priorities are free from possible compromises from the less important ones.
- For each objective, the “satisfactory” levels allow the path decision algorithm to be sensitive to the entities (e.g., targets in the tracking layer, sectors in the search layer) that demand more attention.
- The layered decision framework allows different path decision strategies to be used for the objectives, which leads to improved efficiency.
- Potential savings in computation can be achieved, when a path decision is determined by the first few decision layers, since the remaining layers do not need to be evaluated.

IV. Multi-step Look-ahead Path Decision Strategy for UAV Navigation

An important objective for the path decision algorithm is to navigate the UAV group safely in the surveillance region. In [16] the survival probabilities of the UAVs are incorporated into the global objective function through the

[1] In actual simulations, the differences between different control options are much smaller than those shown in this example. However, by always following the best control option, the UAVs will navigate to desired positions by capturing the gradient information of the objective functions.

TABLE I

DECISION LAYERS IN THE PATH DECISION ALGORITHM FOR THE SURVEILLANCE

Objective	Decision Layer (priority)	Satisfactory level	Evaluation criterion for the accomplishment
Safe Navigation	1	τ_{PS}	$\min\{\pi_S(s), \tau_{PS}\}$
Classification	2	τ_{CLS}	$\min\{\max\{\mu_j\}, \tau_{CLS}\}$
Tracking	3	$\tau_{MSE}(j)$	$\max\{MSE(j), \tau_{MSE}(j)\}$
Search	4	τ_{PNNT}	$\min\{P_{m,n}, \tau_{PNNT}\}$
s is the index of the UAVs and j is the index of the targets.			

TABLE II

DECISION LAYER 1: CONTROL DECISIONS FOR SAFE NAVIGATION WITH $N = 2$ UAVS AND $\tau_{PS} = 0.9$

Control index	(1,1)	(1,2)	(1,3)	(2,1)	(2,2)	(2,3)	(3,1)	(3,2)	(3,3)
$\hat{\pi}_S$	0.92	0.95	0.87	0.99	0.82	0.81	0.93	0.83	0.91
(Expected π_S at k+1)	1	0.98	0.91	0.92	0.87	0.95	1	0.91	0.92
$\bar{\pi}_S$	0.9	0.9	0.87	0.9	0.82	0.81	0.9	0.83	0.9
$(\min\{\hat{\pi}_S, \tau_{PS}\})$	0.9	0.9	0.9	0.9	0.87	0.9	0.9	0.9	0.9
Control Evaluation	0.81	0.81	0.783	0.81	0.713	0.729	0.81	0.747	0.81
$(\prod \bar{\pi}_S(s))$	$\surd$	$\surd$		$\surd$			$\surd$		$\surd$

track update as

$$
\begin{aligned}
&\hat{I}_j(k+1|k+1) = I_j(k+1|k) \\
&\quad + \sum_{s=1}^{N} \{\hat{\pi}_S(s,k+1)\hat{\pi}_D(s,j,k+1) \\
&\quad \cdot \hat{H}(s,j,k+1)' \hat{R}(s,j,k+1)^{-1} \hat{H}(s,j,k+1)\} \qquad (3)
\end{aligned}
$$

which is a variation of (1). If the expected survival probabilities of the UAVs, $\hat{\pi}_S(s, k+1)$, drop, there will be a reduction in the expected information gain. As a result, the path decision algorithm tends to avoid drops in the survival probabilities of the UAVs. While this formulation intuitively makes sense, it turns out to be incapable of preventing the UAV survival probabilities from significant drops. There are two reasons for this problem. First, tracking and safe navigation are two competing objectives. Particularly when a UAV is tracking a single target it tends to get close to the target, while safe navigation requires the UAV to keep adequate distance from the target. The combination of the objectives into a single global objective function can lead to unpredictable compromises. This problem can be solved using the layered decision framework. Second, due to limited maneuverability of the UAV, a one-step look-ahead path decision strategy can result in late detections of potential risks. In this section, a multi-step look-ahead path decision strategy is proposed based on a Roll-out Policy [3]. When used in the decision layer of safe navigation, it is shown to produce significantly improved results.

A. Multi-step Look-ahead Path Decision and Roll-out Policy

By discretizing the controls of the UAVs, multi-step look-ahead path decision for the UAV group can be viewed as a combinatorial optimization problem. However, the problem is NP-hard, e.g., for a UAV group that consists of N UAVs, the optimal solution for a K-step look-ahead path decision needs to consider D^{NK} possible paths, which can be far too expensive for a real-time algorithm even with modest N and K. Instead of seeking the optimal solution, a suboptimal solution requiring less computation is much more desirable. A Roll-out policy, proposed in [3], is a suboptimal solution to combinatorial optimization problems. Based on a heuristic solution to the problem (called a base heuristic), the Roll-out policy is guaranteed to find a solution that is no worse than the base heuristic. Successful applications of the Roll-out policy can be found in [4], [18], in which it works surprisingly well by producing near-optimal solutions.

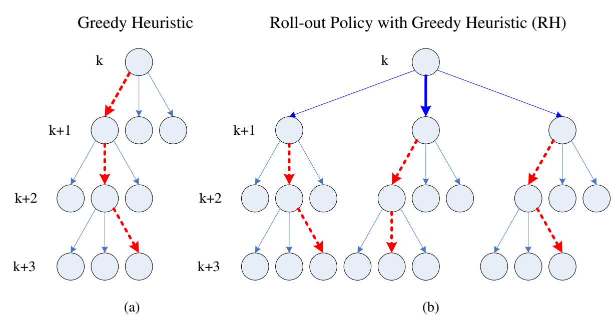

Fig. 1. Greedy Heuristic and Roll-out Policy

Fig. 1 illustrates the greedy heuristic and the corresponding Roll-out policy in a 3-step look-ahead path decision strategy for a single UAV. Assume that at each node, there are 3 controls (turn rates) available for the UAV. Using the Greedy heuristic, the control that leads to the next "node" with the best immediate result will be selected. Fig. 1(a) shows the path (control sequence) from k to $k+K$ $(= k+3)$ generated by the Greedy heuristic (highlighted by the thick dashed arrows). In the Roll-out policy, as shown in Fig. 1(b), instead of starting from k, the greedy heuristic starts from $k+1$ to generate the remaining paths to $k+3$. The control at k that produces the best path to $k+3$ (highlighted by the thick arrow) is selected as the control decision. Notice that the evaluations of the paths from k to $k+K$ are based on the information available at k and the procedure is repeated at every decision time with the updated information. Compared to the exhaustive search, which requires one to evaluate $\sum_{i=1}^{K} D^{N\cdot i}$ "nodes", the Roll-out policy only evaluates $D^N + (K-1)D^{2N}$ nodes. The computational cost increases linearly with the decision horizon K.

B. The Decision Layer of Safe Navigation

The proposed multi-step look-ahead path decision strategy can be used in any decision layer in the layered decision framework (see Section III). Again, instead of seeking one best control decision at k, at each decision layer, the path decision algorithm looks for m best controls which will be passed on to the next decision layer for further selection. An important issue in the K-step lookahead path decision algorithm is to evaluate and compare the control sequences from k to $k+K$. Fig. 1 shows that the evaluation of a control sequence from k to $k+K$ requires the evaluations of the nodes from $k+1$ to $k+K$. In the layer of safe navigation, a node at $k+i$ can be evaluated by

$$\hat{J}_S(k+i) = \sum_s \ln(\min\{\hat{\pi}_S(s,k+i), \tau_{PS}\}) \tag{4}$$

where s is the index of the UAVs and τ_{PS} is the satisfactory level introduced in Table II. Accordingly, the evaluation of a control sequence from k to $k+K$ involves computing

$$\sum_{i=1}^{K} \hat{J}_S(k+i) \tag{5}$$

In addition, a control sequence is considered to be "safe" if the expected survival probabilities of the UAVs are above τ_{PS} along the path, namely,

$$\min_s\{\hat{\pi}_S(s,k+i)\} \geq \tau_{PS} \quad \forall\, i = 1, ..., K \tag{6}$$

Therefore, all "safe" control sequences satisfy

$$\sum_{i=1}^{K} \hat{J}_S(k+i) = KN\ln(\tau_{PS}) \tag{7}$$

Based on above definitions, at the kth decision time, the procedure for a K-step look ahead path decision algorithm for safe navigation is as follows:

- Use the Roll-out Policy to generate control sequences from k to $k+K$.
- If more than one "safe" control sequences that satisfy (7) are detected, pass the controls at k from the "safe" control sequences to the next decision layer.
- Otherwise, the control at k that leads to the "best" control sequence (evaluated using (5)) is selected as the path decision. The evaluations in the remaining decision layers are not needed.

C. Simulation Results for UAV Safe Navigation: Roll-out vs. One-step Look-ahead

Consider first a "toy example" in which one UAV searches and tracks one target. For simplicity, classification is not included here. Table III shows the decision layers of the path decision algorithm.[2] Notice that τ_{MSE} in the tracking layer is set to zero, which means once the target is detected, the UAV will "focus" on tracking. The surveillance region is $40\,\mathrm{km}\times 40\,\mathrm{km}$ and is divided into 10×10 sectors. The target starts from $[2000,\ 14200]\,\mathrm{m}$ with initial velocity $[10,\ -2]\,\mathrm{m/s}$. The process noise of the target has intensity $\sqrt{q} = 0.01\,\mathrm{m/s^2}$. It is assumed that $V_{\mathrm{UAV}} = 40\,\mathrm{m/s}$ and the control set is $\{-3,\ 0,\ 3\}\,\mathrm{deg/s}$. The on board GMTI radar has measurement standard deviations of $[10\,\mathrm{m},\ 1\,\mathrm{mrad},\ 1\,\mathrm{m/s}]$. There are 3 stationary threats located at $[5000,\ 15000]\,\mathrm{m}$, $[7000,\ 7000]\,\mathrm{m}$ and $[20000,\ 10000]\,\mathrm{m}$ (indicated by the "asterisks"). The circles show the boundaries of the corresponding restricted zones within which the survival probability of the UAV from the threat is below the satisfactory level τ_{PS}.

For comparison purposes, the combined objective approach, in which the survival probability of the UAV is incorporated into the expected track update as (3), is also tested. Notice that in the layered decision framework, safe navigation is treated separately from the objective of tracking; thus, unlike (3), the objective of the expected track update given in (1) does not deal with survival probabilities of the UAVs. A modified version of (3)

$$\begin{aligned}\hat{I}_j(k+1|k+1) = \min_s\{\hat{\pi}_S(s,k+1)\}I_j(k+1|k) \\ + \sum_{s=1}^{N}\{\hat{\pi}_S(s,k+1)\hat{\pi}_D(s,j,k+1) \\ \cdot \hat{H}(s,j,k+1)'\hat{R}(s,j,k+1)^{-1}\hat{H}(s,j,k+1)\}\end{aligned} \tag{8}$$

is tested as well, which puts more penalty to the drops in the survival probabilities.

Fig. 2 shows trajectories of the UAV and the target in one simulation.

Figs. 3–4 show the minimum survival probability of the UAV over 100 MC runs, in which "combined objective 1" refers to the approach that uses the expected update in (3) as the objective function and "combined objective 2" refers to the approach that uses the expected update (8) as the objective function. As shown in Fig. 3, the one-step look-ahead path decision strategy cannot meet the requirement for safe navigation, no matter which setting is used. In Fig. 4, although a 9-step look-ahead path decision strategy is used, significant drops in the survival probability of the UAV are still observed in the two combined objective approaches. Only the 9-step look-ahead path decision strategy with the layered decision framework is able to keep the survival probability of the UAV close to the satisfactory threshold of $\tau_{PS} = 0.9$. The rare drop to 0.8 occurred only once in

[2] If the tactical value of the information is very high, safe navigation can be moved to a layer with lower priority.

TABLE III
DECISION LAYERS IN THE SIMULATION

Objective	Decision layer (priority)	Satisfactory level	Evaluation Criterion for the accomplishment	Strategy for path decision
Safe Navigation	1	$\tau_{PS} = 0.9$	$\min\{\pi_S(s), \tau_{PS}\}$	multi-step
Tracking	2	$\tau_{MSE} = 0\,\mathrm{m}^2$	$\max\{MSE(j), \tau_{MSE}\}$	one-step
Search	3	$\tau_{PNNT} = 1$	$\min\{P_{m,n}, \tau_{PNNT}\}$	one-step

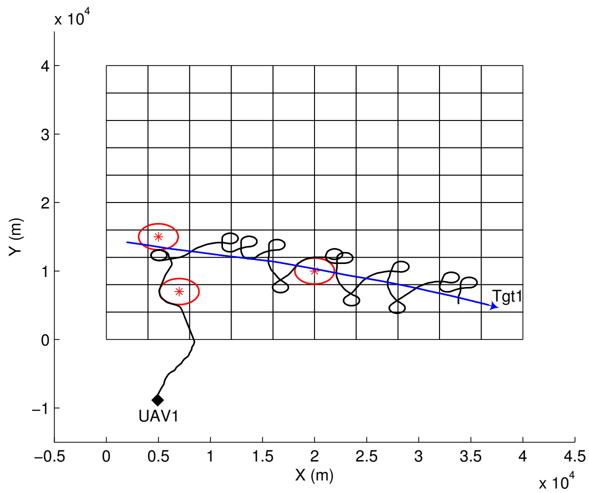

Fig. 2. UAV Trajectory in one Simulation

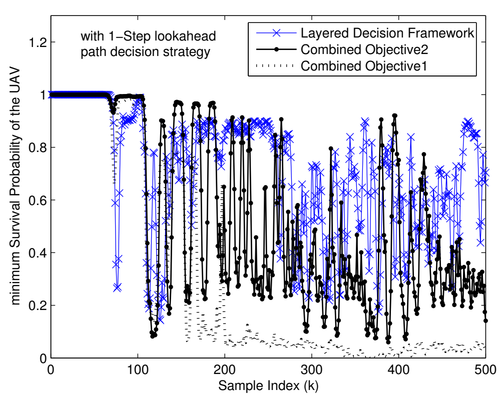

Fig. 3. Minimum survival probability (one-step look-ahead, 100 MC runs)

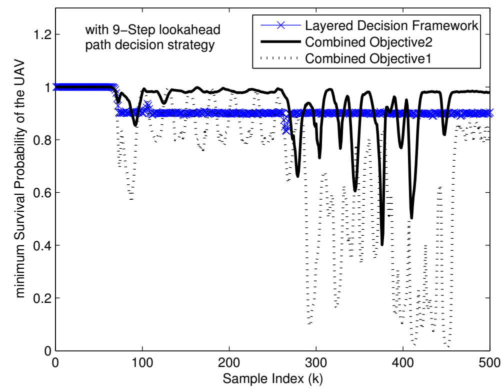

Fig. 4. Minimum survival probability (9-step look-ahead, 100 MC runs)

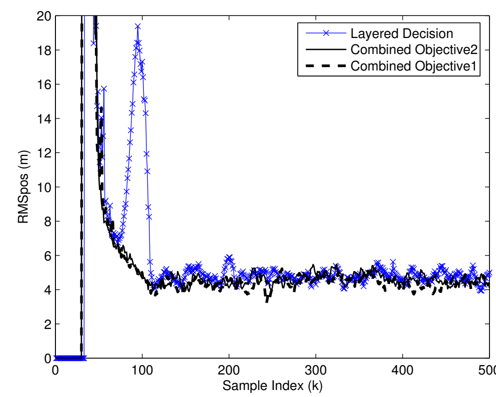

Fig. 5. Track RMS position error (9-step look-ahead, 100 MC runs)

the 100 runs. Fig. 5 compares the RMS position errors of the algorithms. Notice that, around the 100th decision time, the layered decision framework has larger RMS position errors than those of combined objective function approaches, but the drops in the survival probability are avoided, as shown in Fig. 4. This is an example where an objective with higher priority (safe navigation) will not be compromised by objectives with lower priorities (tracking and search), which is a desirable feature of the layered decision framework. Also notice that, most of the time, the three approaches have no significant differences in the RMS position errors.

V. MULTIPLE UAV COOPERATIVE PATH DECISION ALGORITHM FOR SURVEILLANCE MISSIONS

The multi-step look-ahead path decision algorithm proposed in Section IV has no limitation on the number of UAVs. However, its complexity increases exponentially as the number of UAVs increases. To contain the computational complexity of the path decision algorithm, clustering of UAVs into small decision groups can be used. Also, when guiding a group of UAVs, the function of assigning different tasks to different UAVs is of interest. These two functions can be easily incorporated into the Layered Decision framework. Details of the implementations are provided in [20], where the effectiveness of the proposed algorithm is evaluated in a surveillance scenario with 4 UAVs and 4 targets as in Fig.

6. It is shown that the proposed path decision algorithm for

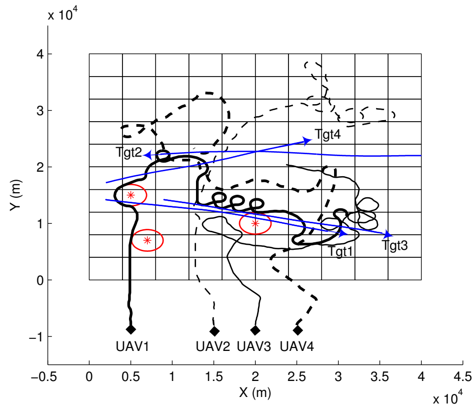

Fig. 6. UAV trajectories in one simulation (three exclusion zones are around the "asterisks")

UAV group is able, with moderate complexity, to (i) guide a group of UAVs cooperatively for surveillance missions with competing objectives, and (ii) achieve balanced performance according to a prioritized list of objectives.

VI. Conclusions

In this paper, the problem of guiding a group of Unmmaned Aerial Vehicles (UAV) for a multi-objective surveillance mission in a hostile environment is studied. First, the control of the UAV is discretized into a finite set, which amounts to sampling the objective functions over the continuous control space. The comparisons of the sample values are able to capture the gradient information in the objective functions, thus guiding the UAV group for the surveillance task.

More importantly, the discretization of the control variables provides extra freedom in dealing with multiple objectives in the surveillance mission. This leads to a layered decision framework, in which different objectives are treated in separate decision layers in the order of their priorities. Compared to the approach that uses a single global objective function which is a combination of all the objectives, the layered decision framework has the following advantages: i) Multiple objectives in the surveillance mission are isolated; thus objectives with higher priorities are free from possible compromises from the less important ones; ii) For each objective, the path decision algorithm is more sensitive to the entities (targets in tracking, sectors in search) that demand more attention; iii) Suitable path decision strategies can be used for different objectives, which makes the algorithm computationally efficient.

The discretized controls also allow the extension of the time horizon of the path decisions, which is particularly important for the safe navigation of the UAVs. A multi-step look-ahead path decision strategy based on the Rollout policy is proposed. When used in the layered decision framework, this approach produces significantly improved results over the one-step look-ahead policy.

For the control of a group of UAV, the use of small path-decision groups and assigning different objectives to different UAVs can also be incorporated, which make the algorithm more flexible. The proposed path decision algorithm is shown to guide a group of UAVs efficiently and safely for the multi-objective surveillance mission considered.

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