A Game Theoretic Data Fusion Aided Path Planning Approach for Cooperative UAV ISR

Dan Shen and Genshe Chen
Intelligent Automation, Inc.
Rockville, MD 20855
{dshen, gchen}@i-a-i.com

Jose B. Cruz, Jr.
The Ohio State University
Columbus, OH 43210
cruz@ece.osu.edu

Erik Blasch
AFRL/RYAA,
WPAFB, OH 45433
erik.blasch@wpafb.af.mil

Abstract—Cooperative and intelligent path planning is important for UAVs to carry out coordinated Intelligence, Surveillance and Reconnaissance (ISR) in adversarial environments. In this paper, we propose a game theoretic data fusion aided platform routing algorithm for cooperative ISR. Our approach consists of three closely coupled components: *1) Closed-loop data fusion*. The Level 1 (Object), Level 2 (Situation) and Level 3 (threat) data fusion form a closed-loop structure, in which Markov game theoretic intent inferences will execute from the results of Level 1 and Level 2 results. The estimated threat intents will be fed back to the Level 2 fusion to improve the performance of the entity aggregation. *2) Cooperative platform routing based on Pareto-optimization, social foraging, and cooperative jamming.* Given the threat information including the threat intents from the data fusion module, a Pareto-optimal problem is formed and Graph-cut based fast solution serves as a reference trajectory for a foraging algorithm, which further dynamically refines the reference path to avoid pop-up obstacles detected along the planned path. 3) *Display/Monitor Module*, in which relevant threats and constraints information are indicated, the terrain data are shown, and current real route and planned route are highlighted, compared, and evaluated. The commander's suggestions can be inputted in this mode.[1 2]

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1. INTRODUCTION

Cooperative and intelligent path planning is important for UAVs to carry out coordinated Intelligence, Surveillance and Reconnaissance (ISR) in adversarial environments. With the significant growth in UAV platforms and data fusion technologies, it is promising to integrate the threat intent inferences (Level 3 data fusion, threat refinement [9]) into the routing generation module so that the planned ISR path can take into account (future) threat actions.

There are two main tasks in ISR routing: *threat intent inference* and *cooperative platform routing*. For the first task, multi-source data from wide-body and UAV on-board sensors should (i) be parsed and classified to form entities (Level 1 data fusion, object refinement); (ii) be clustered to find the relations between them (Level 2 data fusion, situation refinement); (iii) be assigned and evaluated the threat intent hypotheses (Level 3 data fusion, threat refinement). To solve the second task (cooperative path planning), we should divide all threats into two general classes: 1) normal threats (e.g. stationary radars and moving surface-to-air (SAM) sites); and 2) pop-up threats encountered during flight. For the first class of threats, a path planning algorithm is needed to generate waypoints to minimize risk and improve ISR performance. A reactive algorithm should be designed to respond to pop-up obstacles detected while the UAVs fly along the optimal planned path. The two main tasks are coupled because different data fusion results will affect the path generation, which takes the into account threat intents. On the other hand, threats will take different actions to the same UAVs flying different paths, and then the threat intent updates to the data fusion will be altered.

In this paper, we propose a game theoretic data fusion aided platform routing algorithm for cooperative ISR. Our approach consists of three closely coupled components (see Fig. 1): *1) Closed-loop data fusion*. The L1, L2 and L3 data fusion form a closed-loop structure, in which the Markov game theoretic intent inference [3] (L3 data fusion) will be executed from the results of L1 and L2 results. The estimated threat intents will be feed back to the L2 fusion to improve the performance of the entity aggregation in the sense that threat intents will make the entity aggregation based on same intents possible. The performance of the data fusion is evaluated according to the complimentary Metrics [12]. *2) Cooperative platform routing based on Pareto-optimization*, *social foraging* [13], *and cooperative jamming* [15]. Given the threat information including the threat intents from the data fusion module, a Pareto-optimal problem is formed and the Graph-cut based fast solution serves as a reference trajectory for the foraging algorithm, which further dynamically refines the reference path to

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avoid pop-up obstacles detected along the planned path. 3) *Display/Monitor Module*, in which the relevant threats and constraints information are indicated, the terrain data are shown, and the current real route and planned route are highlighted, compared, and evaluated. The commander can make suggestions in this mode.

Our proposed system goes beyond conventional aircraft re-routing algorithms ([4]-[8]) to integrate Markov game theoretical threat intent inference, cooperative jamming, and information visualization in a hierarchical and efficient framework, in which the threat intent inference and path planning modules are called manually by the commander (user) or automatically by the display module based on the performance of current planned path.

The rest of the paper is organized as follows. Section 2 describes our proposed framework. Section 3 presents a Markov model for cyber network defense. In Section 4, a cooperative path planning algorithm is revised to incorporate the adversary intents and flight space partition based on cooperative jamming. Section 5 and Section 6 are for the discussion of simulation results and conclusion remarks.

2. FRAMEWORK

The framework of our proposed approach for platform routing is shown in Fig. 1. There are four main parts: 1) *Cooperative jamming and threat intent integrated path planning algorithm*; 2) *Markov game theoretical intent inference for adversary dynamic threats*; 3) *Information visualization and performance evaluation* based display/monitor module; and 4) *Ontology and graphical model based information design and representation* for threat, terrain, and constraints. The commander (user) experiences and suggestions as well as the evaluation results are fed back to the adversary threat intent inference part to adjust the parameters in the Markov game model, which is efficiently represented and calculated by graphical methods.

Cooperative path planning is the guidance of a group of agents - in our case, a team of UAVs - from a source to a destination of interest, while minimizing the risks from all encountered threats. In our approach, we form a Pareto-optimal cost function based on cooperative jamming and threats/terrain/constraint information. Then we build a directed graph from the objective function, and apply a graph cut (min cut) fast but approximate method [10] to the graph and obtain a max flow path composed of safe flight waypoints. The combination of Cooperative jamming, threat intents, Pareto-optimization, and Graph Cut solution may achieve a convergent, fast, smooth, safe, and efficient path search mechanism.

In order to carry out the threat intent inference, we proposed a closed-loop data fusion module with a Fuzzy Petri Net [14] based level 1 fusion, a hierarchical entity aggregation (HEI) [2] based level 2 data fusion, and a Markov game theoretic level 3 data fusion. Markov game theoretical approaches are more realistic for modeling the dynamics of the system with the presence of intelligent threats. We propose a graphical model to represent the structure and evolution of the above-mentioned Markov game model so that we can efficiently solve the graphical game problem.

In the proposed display/monitor module, the threat, terrain, and constraint information are transferred into forms making use of a human's natural visual and reasoning capability. The planned path (waypoints) and real route are also highlighted so that commander (user) can easily make decisions and suggestions based on his experience in a timely manner. The performance evaluation is integrated to evaluate the performance of the planned path and the result is exploited to trigger the path (re-)planning and threat

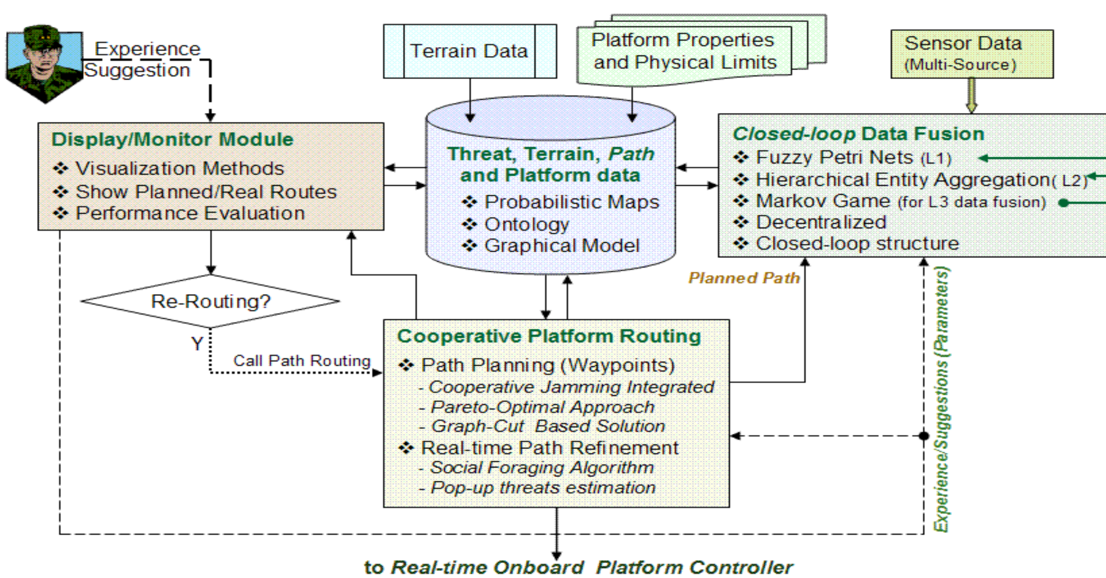

Fig. 1: A game theoretic data fusion aided path planning approach for cooperative ISR

intent inference blocks in Fig. 1 when re-routing is needed.

Ontology and graphical modeling are exploited to design and represent the threat, terrain, trafficability, and constraints information for efficient and sufficient aircraft survivability re-routing in a complex environment. The qualified meta-information [1], such as recency, uncertainties, security, estimates, confidence, cost (availability and time) and pedigree information, is represented by a graphical model so that the meta-information will be easily understood and used by display/monitor and path (re-)planning modules.

In this paper, we will focus on the Markov game theoretic level-3 data fusion and cooperative platform routing parts in the overall framework.

3. A MARKOV GAME MODEL AND SOLUTION

The purpose of the Threat Intent Inference (Level 3 data fusion) is to fuse a group's kinematic and composition information with the intelligence data provided by the lower level data fusion module to infer the group hypothesis intent and Course of Actions (COAs), and focus the analyst's attention on any hostile enemy activities. This process is performed in two steps. First, we compute/update a group hypothesis factlet list. Then, we match each group's factlet list against a probabilistic state transition model representing abstract adversary COAs, and find the most likely one.

To estimate the intent of the dynamic and intelligent threats tracked by the sensor network, we present a Markov game model. In general, a Markov (stochastic) game is specified by (*i*) a finite set of players N, (*ii*) a set of states S, (*iii*) for every player $i \in N$, a finite set of available actions D^i (we denote the overall action space $D = \times_{i \in N} D^i$), (*iv*) a transition rule $q: S \times D \rightarrow \Delta(S)$, (where $\Delta(S)$ is the space of all probability distributions over S), and (*v*) a payoff function $r: S \times D \rightarrow R^N$. For the intent inference and defensive strategy generation problem, we briefly introduce the following distributed discrete time Markov game model (a similar and more detailed model for cyber network defense is published in [16]):

Players (Decision Makers)

All clusters of enemy (or friendly force or neutral force) can be considered as a single player since they have a common overall objective.

State Space

All the possible COAs for enemy and friendly force consist of the state space. An element $s \in S$ is composed of a set of triplets (*resource*, *action*, and *objective*). $s = (s^B, s^R, s^W)$ and $S = s^B \times s^R \times s^W$, where $s^B \in S^B$ is the COAs of Blue (friendly) force and

$$s^B = \left\{ \left(r_i^B, a_i^B, o_i^B \right) | r_i^B \in R^B, a_i^B \in A^B, o_i^B \in O^B \right\} \tag{1}$$

where R^B, A^B and O^B are the set of the resource, action, and objective of blue force, respectively. Similarly, $s^R \in S^R$ is the COAs of Red (enemy) force and

$$s^B = \left\{ \left(r_i^R, a_i^R, o_i^R \right) | r_i^R \in R^R, a_i^R \in A^R, o_i^R \in O^R \right\} \tag{2}$$

Action Space

At every time step, each blue group choose a list of targets with associated actions and confidences (note that: probability distribution over the list of targets, i.e., the sum of the confidences should be equal to 1) based on its local space information, such as the unit type and positions of possible targets, from level-two data fusion.

Transition rule

The objective of the transition rule is to calculate the probability distribution over the state space $q(s_{k+1} | s_k, u_k^B, u_k^R, u_k^W)$, where s_k, s_{k+1} are system states at time k and $k+1$ respectively, u_k^B, u_k^R, u_k^W are the overall utility decisions of the blue team, the red team and the white team, respectively, at time step k.

Payoff Functions

In our proposed decentralized Markov game model, there are two levels of payoff function for each player (enemy or friendly force).

The lower (local) level payoff functions are used by each team or cluster to determine the team actions based on the local information. The top (global) level payoff functions are used to evaluate the overall performance of each player. In our approach, the lower lever payoffs are calculated distributed and sent back to commander/supervisor via communication networks.

Remark 1: *In our Markov game model, the states used in control strategies is the estimates of the future systems states. These estimates will evaluate or update following the Markov Decision Processes (MDPs) in the Markov game framework, in which the interactions are considered. At each time k, the process will be repeated based on the observed current system states.*

Solution to Markov Games

Markov games are more complicated than MDPs in the following two points: 1) each Markov game has more than one decision makers while every MDP only has one player to apply the action inputs, and the transition rule is affected by all of action inputs from the Markov game players; 2) instead of maximizing one objective function in each MDP, the solution to a Markov game has to optimize at least two separate objective functions. To the best of our knowledge, there are no existing solutions to multi-player Markov games. In this section, we provided a procedure for calculating the Mixed Nash solutions to general Markov games.

For the Markov game model specified in this section, we have conducted a procedure to compute the mixed Nash strategies with *K*-step look-ahead horizon. We first convert the Markov game to several MDPs (one MDP for each player with every possible combination of *K*-step strategies of other players) and several one-step static matrix games (one game for each player at every current system state). Then existing algorithms will be exploited to solve the MDPs and matrix games.

Our procedure has the following three advantages: first, it decomposes the complex Markov games into well-understood MDPs and static matrix games. Second, it uses existing algorithms and the existence of a K-step look-ahead optimal solution is guaranteed. Third, the learning and partial operability of the Markov game model can be addressed via the existing *Q*-learning algorithms of Partial Observable Markov Decision Process (POMDP).

4. Cooperative Path Planning Algorithm

In this section, a cooperative jamming and threat intent integrated path planning algorithm is presented to determine a route for a group of UAVs that minimize their risk of being tracked and destroyed by threats such as SAM sites during the mission of cooperative ISR. Cooperative jamming [15] for path planning can efficiently provide the concealment for aircrafts so that they can, when necessary, safely penetrate a heavily defended region. The threat intent represented by the course of actions (COA) is well formulated in the framework of Pareto optimization, which is useful when we consider cooperative objectives in a team. Our approach provides an efficient way to include threat analysis support into the path planning process.

Cooperative Jamming

The cooperative jamming problem is well address by Kim and Hespanha [15]. We will incorporate their work in our path planning algorithm. In this subsection, we briefly review the work.

Cooperative jamming, which make use of the network-Centric paradigm by exploiting multiple platforms to gain geometric, physical and tactical advantage by employing multiple platform techniques, has received great interest in recent years. Jamming is typically classified as: self-protection or support depending on whether it is used to protect the aircraft that transmits the Electronic Counter-Measures (ECM) noise signal or a different aircraft. As shown in Fig.2, UAV D is engaged in self-protection jamming, while UAV A, B, and C are performing support jamming between them. Note that the electronic counter measure (ECM) signal from the D-labeled UAV may also provide some form of concealment for A, B, and C, however this kind of concealment is less efficient because the ECM signal is transmitted from outside the main lobe of the antenna that is rotating and being used to track the other aircrafts at a fixed time.

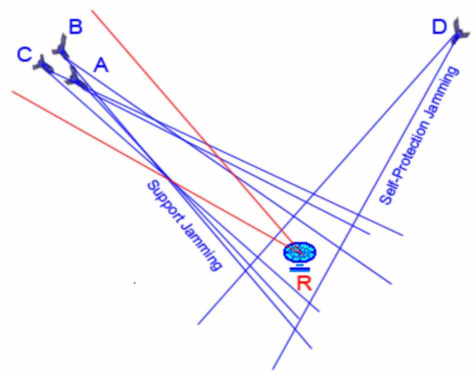

Fig.2: Cooperative Jamming

Based on the effectiveness of active (transmitting) ECM devices (represented by a function of the Jamming to Signal ratio (J/S) [11]), the whole flight space can be partitioned into four parts:

- Region 1: jamming will never be effective;
- Region 2: jamming will only be effective for limited values of both the azimuth and the elevation angles;
- Region 3: jamming can be effective for any direction of motion (azimuth), provided that the elevation is appropriately selected;
- Region 4: jamming is always effective regardless of the azimuth and the elevation angles.

It is straightforward to extend this approach to multi-threat case. The main advantage of the proposed cooperative jamming algorithm for path planning is to partition the whole flight space into four above-mentioned distinct parts. Then in path planning stage, we can separately consider them and assign different values to the parameters in path planning algorithm

Pareto-Optimal Cost Function for Path Planning

Given a region $\Re \in R^3$ populated by multiple SAM sites, minimum-risk path planning refers to the computation of a path $\rho: [0,T] \rightarrow \Re$ for the group of *m* aircrafts that starts at an initial position x_i and ends at a final position x_f , maximizing the probability that the aircrafts will not be killed by any of the threats and will therefore survive the path. There is the distance of the missile reach distance needed.

The concept of a Pareto-optimal strategy is useful when we consider cooperative strategies in a team. For simplicity, let us consider a team with three members *X*, *Y*, and *Z*, each with a separate objective function that depends on the decision variables *x*, *y*, and *z* of all members of the team. A set of decision choices x_p, y_p, and z_p is said to be Pareto-optimal if for any other set of choices of decisions resulting in an improvement for a team member, also results in another member being worse off. There are usually infinitely many sets of Pareto-optimal decision variables. Pareto-optimal decision variables can be computed by minimizing a weighted convex linear combination of the objective functions. The minimizing decision variables are Pareto-optimal. By changing the weights, other Pareto-optimal solutions can be found. The weights have to be non-negative and they have to add up to one. If the objective functions are convex, all Pareto-optimal solutions can be found this way.

The single-criterion Pareto-optimal cost function for the group is

$$J[\rho]=\int_0^T \ell\left(\rho(t),\dot{\rho}(t)\right)dt \qquad (3)$$

where, $\ell\left(\rho(t),\dot{\rho}(t)\right)=\sum_{j=1}^{M}\left(\lambda_j\sum_{i=1}^{N}\eta_{ij}(x_j,\dot{x}_j,z_i)\right)$; x_j and z_i are the positions of j^{th} UAV and i^{th} threat, respectively ; η_{ij} is called the risk density for the j^{th} UAV with respect to the i^{th} threat; λ_j denotes the Pareto cooperation coefficients.

To extend our previous work [17] on path planning, we included, in the cost function (Eq 3), the information obtained from adversary intent inference and flight space partition based on cooperative jamming to determine different values of the parameters.

A fast and approximate Graph-Cut solution

In the implementation of the Pareto algorithm we used the graph cut method [10] to save computing time. To improve the efficiency of the traditional even-grid algorithms, a non-uniform sampling mechanism is used. These sampled points will be the nodes of the new graph, which will be handled by graph cut to find the max flow. It can be obtained by using the following procedure:

1) Extract randomly *K* points $P:=\left\{p_k\in R^n : k=1,2,\cdots,K\right\}$ with the spatial probability density over R^n proportional to $\left(\sup_{v\in V}\|\nabla_x\ell(x,v)\|+A\|\nabla_v\ell(x,v)\|\right)^n$ where *v* is the velocity of the group. *V* is the set of all possible values of the velocity. *A* is an upper bound of the second derivative of ρ, i.e. $\|\ddot{\rho}\|\le A$.

2) Construct a directed graph using the points in the set *P* as nodes. The edge cost is calculated in step 3).

3) Assign the edge cost proportional to the reciprocal value of the difference cost between neighboring points. Thus, the min cut will cluster all the dangerous points.

4) Using the algorithm proposed in [10], we can find a max flow for the graph.

5) Build a sampling point set χ by sufficiently finely sampling the flow path created in step 4).

The advantages of our re-path planning can be summarized as follows: 1) Cooperative jamming is investigated to partition the whole flight space into four distinct parts based on the concealments jamming can provide; 2) Pareto-optimal concept is exploited to form the cost function for finding a maximum safe route and treat intents and results from jamming are integrated; and 3) a graph-cut based optimization solution is proposed to solve the cost function speedily and stably.

5. SIMULATIONS AND EXPERIMENTS

Scenario

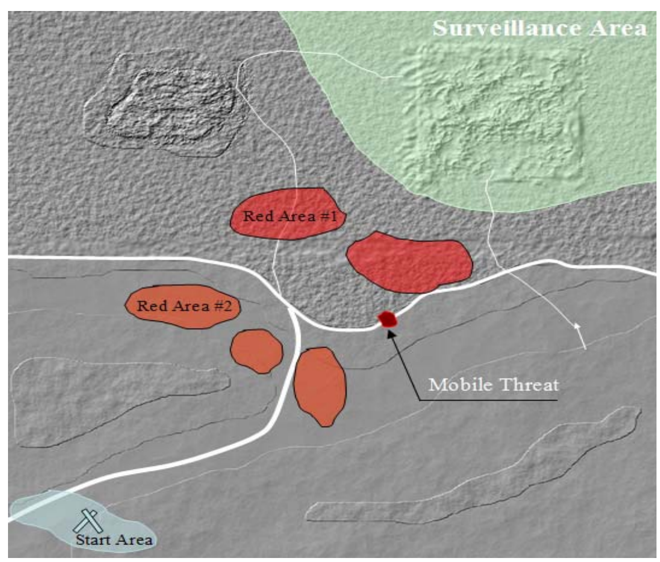

Fig.3. A scenario in a virtual battlefield

Suppose there is a starting area (as shown in Fig.3) in which there are some starting points and a final destination area (for surveillance) in which there are some destination points. Between the starting area and final destination area there are some dangerous areas which have known enemy. Beside them, there are also some possible adversary threats which are also dangerous to UAVs. For UAVs to get to the final destination points as safely as possible, usually UAVs should try to avoid the dangerous areas and the possible adversary threats in their paths. This requires us to model the situation with some comprehensive risk-benefit functions. It is supposed that the adversary threat will be detected during the path execution stage rather than the static path planning stage. The adversary intent will be estimated by our Markov game theoretic data fusion approach.

Simulation Results -Threat Intent Inference

By following the procedure specified in Section 3, we first find the following blue-MDP solution (as shown in Fig.4) to the Markov game with a fixed K=5 pre-fixed actions (dx = 0, -1, 0, 0, -1, dy =-1, 0, -1, -1, -1) for red player. The rewards are shown in Fig.5.

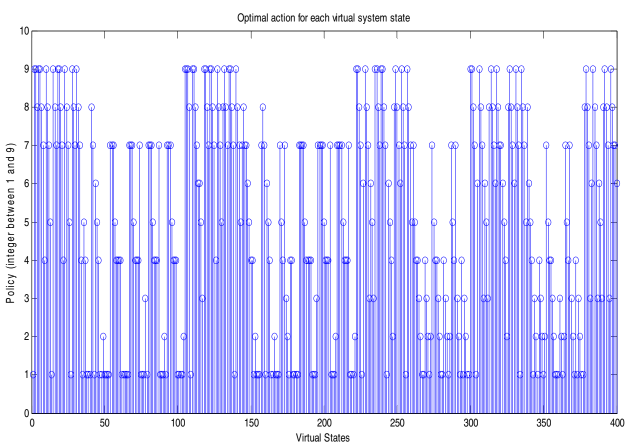

Fig.4: Optimal policy (MDP solution) for blue side with prefixed red course of action.

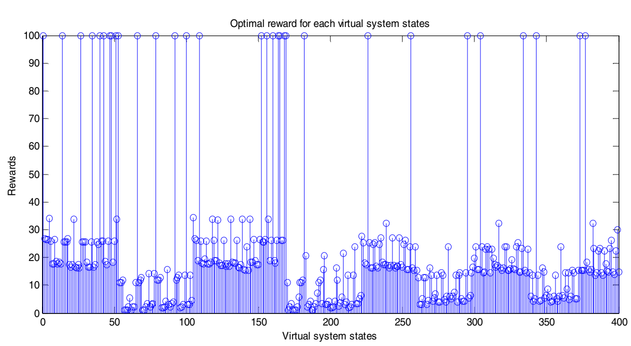

Fig.5: The associated reward for each possible virtual system states.

In the simulation, we divide the *x*-*y* plane into 10×10 grids. For each cell, there are four possible states: 1) No players, 2) blue player, 3) red player, and 4) both players. So there are total 400 virtual system states. For each player, there are 9 possible actions (each d*x* or d*y* has 3 choices:-1, 0, 1).

In Fig.4, we can see the optimal action sequences (up to K-step) of blue force at all possible virtual states given a fixed K = 5 fixed actions (x = 0, -1, 0, 0, -1, y = -1, 0, -1, -1, -1), which can be coded a action sequence (into action space) as 4, 2, 4, 4, 1. For example at virtual state 50 (the corresponding actual state is only blue player is in location x = 4, y = 8), the optimal action is 2, which can be decoded as (dx = -1, dy = 0). The corresponding maximum blue reward for each virtual state is shown in Fig.5. We calculated the blue actions and rewards for all possible K-step red action sequences. Similarly, we can obtain the red actions and rewards given all possible K-step blue action sequences.

The second step is to merge the first K-step actions to form the optimal K-step action sequence. The associated reward is the sum of the K rewards obtained from Fig.4 and Fig.5.

The third step is to form 2-player static bi-matrix games to calculate the (mixed) Nash strategies. The values of the bi-matrix games are from the step 2. For the case K = 1, at system state 12, the reward is 18.3863, and the first action is 7. We have to evolutes the system up to *K-step* to find the required values for blue side. This is based on the optimal blue policy and the pre-fixed red actions. We obtain the following bi-matrix game (as shown in Fig.6) for blue force at system state 12.

Fig.6: A bi-matrix game with solution for state 12.

We found three Nash strategies for state 12. Since mixed strategies have the advantage of confusing opponents, the best solution is #3.

Simulation Results –Cooperative Path Planning

The first step of cooperative platform routing is to conduct static path planning to find the approximate and discrete path composed of way points. This part is based on the Pareto-optimal concept with jamming and adversary intent inference. The max flow obtained using Pareto algorithm and Graph Cut. is shown in Fig.7. It can be seen that some path segments may have excessive turn angle considering the UAV dynamic constraints. This limitation can be eliminated by using the dynamic path execution algorithm -

the Foraging algorithm, as shown in Fig.8. Some reference points obtained from max-flow are also shown in the plot.

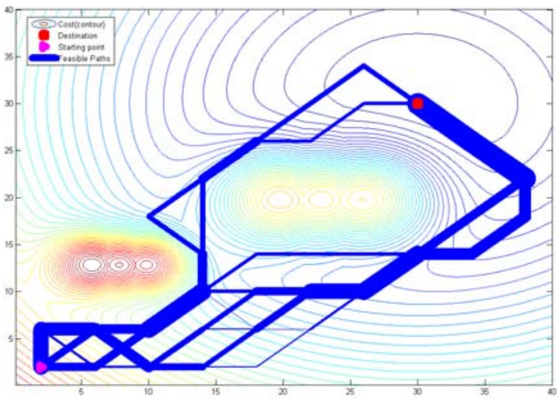

Fig.7: Path Generated by Graph Cut

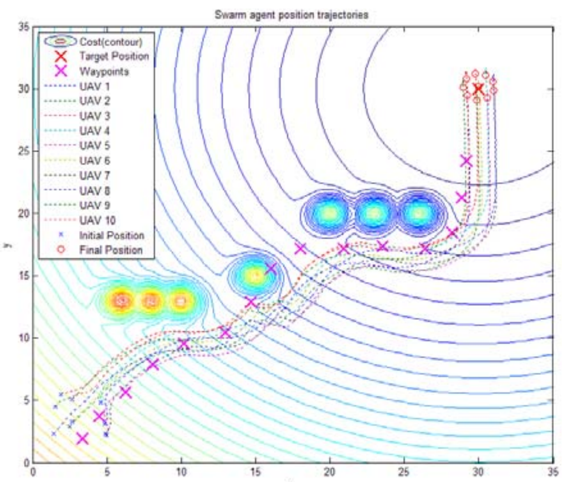

Fig.8: Dynamic path execution based on forging algorithm

From Fig.8, we can see the surveillance path can avoid all the dangerous areas and the mobile threat. The COAs of the mobile threat are estimated by the Markov game theoretic intent inference approach.

6. CONCLUSIONS

In this paper, we have presented a cooperative UAV surveillance routing framework to improve the path planning performance via unifying a Markov game theoretic adversary intent inference and flight space partition based on cooperative jamming strategies. Our original Pareto-Foraging path planning algorithm [17] has been revised and extended to evaluate the feasibility of our proposed game theoretic data fusion aided path planning approach for cooperative UAV ISR.

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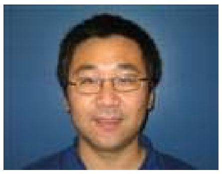
BIOGRAPHY



Dan Shen *received the B.S. degree in Automation from Tsinghua University, Beijing, China, in 1998 and the M.S. degree in electrical engineering from The Ohio State University (OSU), Columbus, in 2003. From 1998 to 2000, he was with Softbrain Software Co., Ltd, Beijing, China, as a Software Engineer. From September 2005 to March 2006, he was an intern at Intelligent Automation, Inc (IAI)., Currently, he is with IAI as a research scientist. His research interests include game theory and its applications, optimal control, and adaptive control.*

Genshe Chen *received his B. S. and M. S. in electrical engineering, Ph. D in aerospace engineering, in 1989, 1991 and 1994 respectively, all from Northwestern Polytechnical University, Xian, P. R. China. He did postdoctoral work at the Beijing University of Aeronautics and Astronautics and Wright State University from 1994 to 1997. He worked at the Institute of Flight Guidance and Control of the Technical University of Braunshweig (Germany) as an Alexander von Humboldt research fellow and at the Flight Division of National Aerospace Laboratory of Japan as a STA fellow from 1997 to 2001. He was a Postdoctoral Research Associate in the Department of Electrical and Computer Engineering of The Ohio State University from 2002 to 2004. Since February 2004, Dr. Chen has been with the Intelligent Automation, Inc., Rockville, MD. He has served as the Principal Investigator/Technical lead for more than 15 different projects, including maneuvering target detection and tracking, joint ATR and tracking, cooperative control for teamed unmanned aerial vehicles, a stochastic differential pursuit-evasion game with multiple players, multi-missile interception, asymmetric threat detection and prediction, space situation awareness, and cyber defense, etc. He is currently the program manager in Networks, Systems and Control, leading research and development efforts in target tracking, information fusion and cooperative control. His research interests include guidance and control of aerospace vehicle, GPS/INS/image integrated navigation systems, target tracking and information fusion, cooperative control and optimization for military operations, computational intelligence and data mining, hybrid system theory and Markov chain, signal processing and computer vision, cooperative and non-cooperative game theory, Bayesian networks, Influence Diagram, and GIS.*

Jose B. Cruz, Jr. *received his B.S. degree in electrical engineering (summa cum laude) from the University of the Philippines (UP) in 1953, the S.M. degree in electrical engineering from the Massachusetts Institute of Technology (MIT), Cambridge in 1956, and the Ph.D. degree in electrical engineering from the University of Illinois, Urbana-Champaign, in 1959. He is currently a Distinguished Professor of Engineering and Professor of Electrical and Computer Engineering at The Ohio State University (OSU), Columbus. Previously, he served as Dean of the College of Engineering at OSU from 1992 to 1997, Professor of electrical and computer engineering at the University of California, Irvine (UCI), from 1986 to 1992, and at the University of Illinois from 1965 to 1986. He was a Visiting Professor at MIT and Harvard University, Cambridge, in 1973, and Visiting Associate Professor at the University of California, Berkeley, from 1964 to 1965. He served as Instructor at UP in 1953–1954, and Research Assistant at MIT from 1954 to 1956. He is the author or coauthor of six books, 21 chapters in research books, and numerous articles in research journals and refereed conference proceedings.*

Dr. Cruz was elected as a member of the National Academy of Engineering (NAE) in 1980. In 2003, he was elected a Corresponding Member of the National Academy of Science and Technology (Philippines). He is a Fellow of the Institute of Electrical and Electronics Engineers, Inc. (IEEE) elected in 1968, a Fellow of the American Association for the Advancement of Science (AAAS), elected 1989, a Fellow of the American Society for Engineering Education (ASEE), elected in 2004, and a Fellow of the International Federation on Automatic Control (IFAC) elected in 2007. He received the Curtis W. McGraw Research Award of ASEE in 1972 and the Halliburton Engineering Education Leadership Award in 1981. He is a Distinguished Member of the IEEE Control Systems Society and received the IEEE Centennial Medal in 1984, the IEEE Richard M. Emberson Award in 1989, the ASEE Centennial Medal in 1993, and the Richard E. Bellman Control Heritage Award, American Automatic Control Council (AACC), 1994. In addition to membership in NAE, ASEE, and AAAS, and IEEE, he is a Member of the Philippine

American Academy for Science and Engineering (Founding member, 1980, President 1982, and Chairman of the Board, 1998–2000), Philippine Engineers and Scientists Organization (PESO), National Society of Professional Engineers, Sigma Xi, Phi Kappa Phi, and Eta Kappa Nu. He served as a Member of the Board of Examiners for Professional Engineers for the State of Illinois, from 1984 to 1986. He served on various professional society boards and editorial boards, and he served as an officer of professional societies, including IEEE, where he was President of the Control Systems Society in 1979, Editor of the IEEE Transactions on Automatic Control, a Member of the Board of Directors from 1980 to 1985, Vice President for Technical Activities in 1982 and 1983, and Vice President for Publication Activities in 1984 and 1985. He served as Chair (2004–2005) of the Engineering Section of the American Association for the Advancement of Science (AAAS).

***Erik Blasch** received his B.S. in mechanical engineering from MIT and Masters in mechanical and industrial engineering from Georgia Tech and MBA, MSEE, from Wright State University and a PhD from WSU in EE. Dr. Blasch also attended Univ of Wisconsin for an MD/PHD in Mech. Eng until being called to Active Duty in the United States Air Force. Currently, he is a Fusion Evaluation Tech Lead for the Air Force Research Laboratory, Adjunct Professor at WSU, and a reserve Maj with the Air Force Office of Scientific Research.*

Dr. Blasch was a founding member of the International Society of Information Fusion (ISIF) and the 2007 ISIF President. Dr. Blasch has many military and civilian career awards; but engineering highlights include team member of the winning ‘91 American Tour del Sol solar car competition, ’94 AIAA mobile robotics contest, and the ’92 AUVs competition where they were first in the world to automatically control a helicopter. Since that time, Dr. Blasch has focused on Automatic Target Recognition, Targeting Tracking, and Information Fusion research compiling 200+ scientific papers and book chapters. He is active in IEEE and SPIE including regional activities, conference boards, journal reviews and scholarship committees.