Game Theoretic Approach to Threat Prediction and Situation Awareness

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The strategy of data fusion has been applied in threat prediction and situation awareness. The terminology has been standardized by the Joint Directors of Laboratories (JDL) in the form of a so-called "JDL Data-Fusion Model." Higher levels of the model call for prediction of future development and awareness of the development of a situation. It is known that the Bayesian Network is an insightful approach to determine optimal strategies against an asymmetric adversarial opponent. However, it lacks the essential adversarial decision processes perspective. In this paper, a data-fusion approach for asymmetric-threat detection and prediction based on advanced knowledge infrastructure and stochastic (Markov) game theory is proposed. Asymmetric and adaptive threats are detected and grouped by intelligent agent and Hierarchical Entity Aggregation in level-two fusion and their intents are predicted by a decentralized Markov (stochastic) game model with deception in level-three fusion. We have evaluated the feasibility of the advanced data fusion algorithm and its effectiveness through extensive simulations.

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1. INTRODUCTION

Data fusion has been largely applied to symmetric military warfare in which long-term strategic target development processes have developed the signatures or deductive model-based templates describing the component targets of the fielded adversary forces [14], [27]. Asymmetric adversaries, usually utilizing Camouflages, Concealment, and Deceptions (CC&D), and "unilateral destruction" are quite unpredictable in their behavior, tactics, weapons, and the choice of targets. Information and patterns of behavior that could provide advanced warning of hostile intent are often hidden in a vast background of harmless civilian activity. Automated processing techniques are needed to augment tactical intelligence-analysis capabilities by automatically identifying the militarily-relevant features of all available data of different modalities (e.g., signals intelligence, human intelligence, imagery intelligence, etc.) and recognizing patterns that are out of the ordinary [25] and/or indicate probable hostile intent [18].

As asymmetric warfare becomes more prevalent and introduces new security challenges, there is a critical need for strategies for providing actionable information to military decision makers so that the adversaries' most likely future courses of actions (COAs) can be predicted. By successfully assessing possible future threats from the adversaries, decision makers can make more effective targeting decisions, plan friendly COAs, mitigate the impact of unexpected adversary actions, and direct sensing systems to observe more efficiently adversary behaviors. Information fusion is an efficient method for providing this information by combining diverse data from multiple sources. Many studies have dealt with the information sources directly, which is the first level of fusion (object assessment) and some have aggregated information for level-two fusion—situation assessment (SA) [22]. Information fusion for threat and situation analysis is outlined in [13] with reference to utility value. Others have included SA from cyber-IF domains [20] with elements of SA ontology developments [16]. However, to combat the present and future asymmetric threats to national and international security, information fusion developments must progress beyond current level-one fusion paradigms.

In this research, we developed a data-fusion framework for asymmetric-threat detection and prediction in an urban-warfare setting based on advanced knowledge infrastructure and Markov (stochastic) game theory. It consists of four closely coupled activities: 1) Level-one fusion automates the processing and integration of information from disparate sources to produce an integrated object state. 2) Level-two fusion automates the estimation and groups the cooperative objects which perform common tasks. The main tasks of level-two fusion are estimation and prediction of relations among entities, to include force structure and cross force relations, communications and perceptual influences, phys-

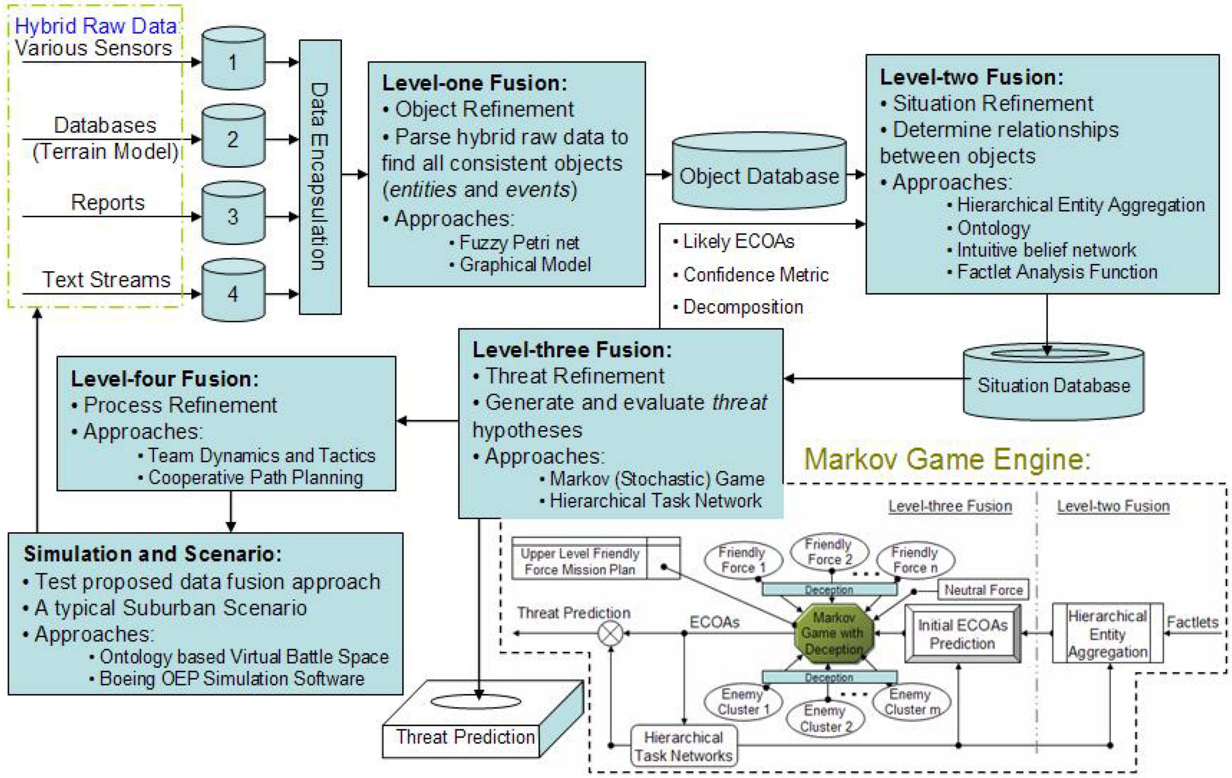

Fig. 1. The overall architecture. (The substructure of the Markov Game engine is also clearly shown in Fig. 2.)

ical context, etc. 3) Level-three fusion automates, infers and predicts the intentions and COAs of asymmetric threats. 4) Level-four fusion uses these COAs to task available sensor assets to optimally minimize cost of operations and decision response time. In particular, asymmetric and adaptive threats are detected and grouped by intelligent agent and Hierarchical Entity Aggregation in level-two fusion and their intents are predicted by a decentralized Markov (stochastic) game model with deception in level-three fusion. Game theory is not a new concept in military and cyber defense decision support. Existing game theoretic approaches [1] [2] [21] for threat detection and decision support are based on static matrix games and simple extensive games, which are usually solved by game trees. However, these matrix game models lack the sophistication to study multi-players with relatively large actions spaces, and large planning horizons. Recently, Brynielsson and Arnborg propose a game theoretic data fusion approach [30] via combining higher level command and control (C2) and Bayesian Network (BN) to solve multiple-decision-makers problems.

We have implemented Hierarchical Entity Aggregation and ontology-based Factlet Analysis Function to detect asymmetric treats at level-two fusion. Factlets are statements or evidence about the situation in the battlespace and they form the main input to the level-two fusion. We have implemented an adversary Markov game [23] model with three players: Red force (enemies), Blue force (friendly forces), and White force (neutral objects) at level-three fusion. Inherent information imperfection is considered and implemented in two methods: 1) the decentralized decision making scheme; and 2) deception with bounded rationality. We have modified our game theoretic sensor management algorithm at level-four fusion.

A software prototype has been developed with a display module based on the *Mixed-Initiative Control of Autonomous Unmanned Units under Uncertainty* (MICA) OEP [28] to integrate levels 1, 2, 3, and 4 data fusion and to demonstrate the performance of our proposed algorithms.

The paper is organized as follows. In Section 2, we will summarize the technical approach, which includes overall architecture, hierarchical entity aggregation at level-two fusion, and Markov game approach at level-three fusion. Section 3 describes the experimental results. Section 4 concludes the paper.

2. THREAT PREDICTION AND SITUATION ANALYSIS

2.1. Overall Structure

The overall architecture of our game theoretic data fusion is shown in Fig. 1. The level-one fusion builds the tracks of enemy targets from the reported data formatted by Data Encapsulation, which is the mechanism whereby the original data are kept hidden from the user and the user can only perform a restricted set of operations on the data. Level-one fusion also writes the Red target track table, which contains time, location, target type beliefs, and other information about each target. The tracks are based on data from the Blue Unmanned Air vehicle (UAV) and Airborne Warning and Control System (AWACS) sensors. Field reports from forward observers and signal intelligence contributes to event data. Level-one fusion establishes and maintains tracks for all ground vehicles, makes track-to-track associations, eliminates duplicates, and also initiates, maintains and drops tracks. The Blue tables of tracks of friendly armament resources contain similar information.

The level-two fusion (situation assessment–SA) performs spatial and temporal processing on tracks produced by level-one multi-sensor, multi-target track fusion, supplemented with intelligence information from both structured data sources such as databases and unstructured data sources such as ontology-based documents. At this level, Hierarchical Entity Aggregation, ontology and Factlet Analysis Function are used to cluster Red entities into groups by position, find the group centers-of-mass, build target group tables, and determine certain critical events and behaviors over time, which it formats into frame structures to pass to the level-three fusion process.

At level-three (threat assessment–TA) fusion, we investigated and demonstrated the effectiveness of Markov game theory. An adversarial Markov game framework is proposed for threat refinement to drive existing and newly formulated models of threat behavior with factlets derived from situation refinement to support the determination of possible enemy course of actions (ECOAs). An artificial intelligence planning concept, Hierarchical Task Network, is exploited to decompose the estimated ECOAs. The decompositions are fed back into and used in level-two fusion to identify and group the enemy entities that pose threats.

At level-four fusion (process refinement), the main tasks are to perform resource allocation and to provide feedback information for fusions at level 1, 2, and 3 to adjust the parameters. We use the method developed by the authors in a Navy funded on-going Phase II project named "Adaptive Cooperative Path and Mission Planning for Multiple Aerial Platforms."

We have conducted the implementation and analysis of several data fusion approaches at every JDL-model level, including conscious effort on the display technology to the user (as proposed in the Data Fusion Information Group (DFIG) [6]). We drive existing and newly formulated algorithms to support the determination of possible enemy COA. Asymmetric threats will be identified efficiently by Hierarchical Entity Aggregation at level-two fusion and assigned special payoff functions in our Markov Game framework at level-three fusion so that the intents of these irrational threats or entities will be efficiently predicted.

Due to page limitations, here we focus only on level-two and level-three data fusion and details can be found in the following subsections. A related paper summarizing our results with respect to level-one fusion algorithm will appear elsewhere.

2.2. Level-Two Fusion—Situation Refinement

The objectives of level-two fusion SA include estimation as to the measurements and observations that are available and establishing relationships between entities, events and the environment. An ontology-based battle-space modeling technique provides feasibility to the representation and organization of the environmental observations in a machine-readable manner. It also facilitates prediction of the potential relationships among the entities.

The Factlet Analysis Functions execute across the extent of the Virtual Battlespace as well as estimate across the objects present and within each analysis perspective, to generate both measured and inferred items of evidence, the "factlets." These Functions are concerned with establishing the "relationships" between objects in the Virtual Battlespace. For example, the Motion Analysis Function considers the movement patterns of groups (established by the Aggregate Analysis Function) of military objects such as armored personnel carriers. The Motion Analysis Function may conclude that the current movement pattern indicates a probing behavior on the part of the adversary, rather than a full scale attack. This prediction becomes a factlet.

In our data-fusion framework, Hierarchical Entity Aggregation [12] [1] [15] (HEA) is exploited to identify and group the entities that pose threats so that level-three TA fusion can be performed efficiently because of the following two major reasons. HEA reduces the ECOA hypothesis space for level-three fusion by reducing the number of potential "threats" to consider. In our approach, applying a Markov (stochastic) game theoretic algorithm to predict ECOA becomes more feasible. The other is that HEA can efficiently identify the asymmetric threats. Entity Aggregation plays an important role in subsequent fusion processing in the way that it provides aggregates that have the same tactical goal. For example, the capabilities and resources of a single terrorist are vastly different from the capabilities and resources of a team of terrorists. As a result, HEA will produce different results when considering a single terrorist or a team of terrorists as a threatening entity. To improve the performance of asymmetric adversary identification, we propose a feedback structure based on a Hierarchical Task Network (HTN) so that the revised asymmetric tactics and strategy can be decomposed and fed back to the HEA.

These identified asymmetric units with the associated aggregations will be handled and refined by

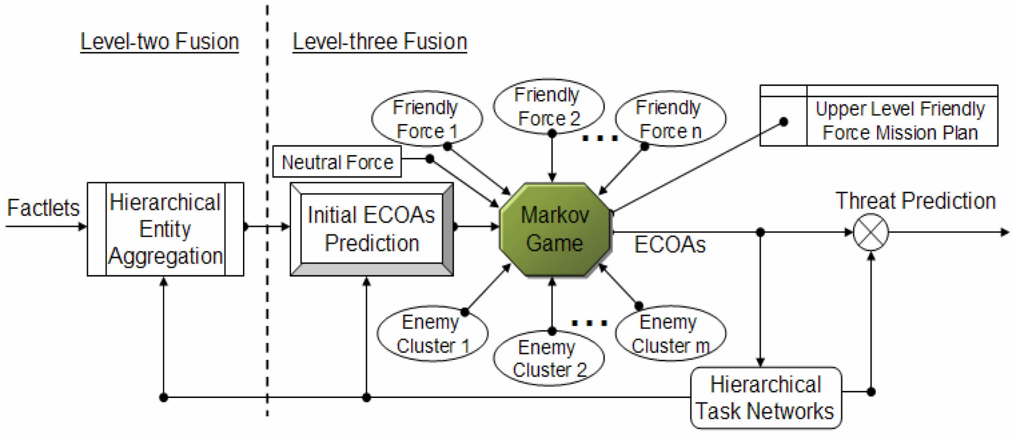

Fig. 2. Structure of level-three fusion (threat refinement).

our proposed Markov games in level-three TA data fusion.

2.3. Level 3 Data Fusion—Threat Refinement

2.3.1. A Decentralized Stochastic Game Theoretical Model

As shown in Fig. 2, a decentralized Markov game is used to model the evolution of ECOAs originated from an initial prediction based on Hierarchical Entity Aggregation.

A Markov (stochastic) game [23] is given by (i) a finite set of players N, (ii) a finite set of states S, (iii) for every player $i \in N$, a finite set of available actions D^i (we denote the overall decision space $D = \times_{i\in N} D^i$, where $\times$ is the multiplication operation), (iv) a transition rule $q : S \times D \to \Delta(S)$, (where $\Delta(S)$ is the space of all probability distributions over S), and (v) a payoff function $r : S \times D \to R^N$. For our threat prediction problem, we obtain the following discrete time Markov game:

Players (Decision Makers)—Although in our distributed (decentralized) Markov game model, each group (cluster, team) makes decisions, there are three main players: enemy, friendly force, and neutral players. All clusters of enemy (friendly force, or neutral) can be considered as a single player since they have a common objective.

State Space—All the possible COAs for enemy and friendly force consist of the state space. An element $s \in S$ is thus a sample of enemy and friendly force COAs composed of a set of triplets (resource, action verb, and objective). As an example, an enemy COA might be: the Red team 1 (resource) attacks (action verb) the Blue team 2 (objective). Similarly, for the friendly force COAs, resource is a friendly asset and objective is an adversary entity. Therefore, we can denote the state and state space as

$$s = (s^B, s^R, s^W)$$

$$S = S^B \times S^R \times S^W$$

where $s^B \in S^B$, $s^R \in S^R$, and $s^W \in S^W$ are the COAs of Blue (friendly) force, Red (enemy) force, and White (neutral) force, respectively.

$s^B = \{(r_i^B, a_i^B, o_i^B) \mid r_i^B \in R^B, a_i^B \in A^B, o_i^B \in O^B\}$ where R^B, A^B and O^B are the set of the resource, action, and objective of Blue force, respectively.

Similarly, the states for red force and white force are denoted as:

$$s^R = \{(r_i^R, a_i^R, o_i^R) \mid r_i^R \in R^R, a_i^R \in A^R, o_i^R \in O^R\}$$

$$s^W = \{(r_i^W, a_i^W, o_i^W) \mid r_i^W \in R^W, a_i^W \in A^W, o_i^W \in O^W\}$$

REMARK 1 It is well known that civilians often play an active role in wars. That is, they are not just passively static but might purposefully take actions to help one side in a battle to minimize their losses or achieve some political purpose. Unfortunately, existing game theoretic models usually do not consider this situation, although collateral damage has been considered in a paper on a two-player game model by Dr. Cruz et al. [10]. In this research, a three-player attrition-type discrete time dynamic game model is formulated with two opposing forces and one civilian player that might be either neutral or slightly biased. In our current implementation, the White units only care about their possible losses. For example, when a dangerous location is detected, normal White units will find a COA to keep themselves as far as possible from the harmful location. In the case where Red force poses as White for deceptive purpose, our algorithm will deem the Red force as White until abnormal activities or deceptions are detected.

Decision—At every time step, each Blue group chooses a list of targets with associated actions and confidences (note that: the probability distribution over the list of targets, i.e., the sum of the confidences should be equal to 1) based on its local battle field information, such as the unit type and positions of possible targets, from level-two data fusion. Let D_i^B denote the decision space of the ith Blue team. Each element d_i^B of D_i^B is defined as

$$d_i^B = \left\{(a_i^B, t_i^B, p_i^B) \mid a_i^B \in A^B, t_i^B \in O^B, 0 < p_i^B \leq 1, \sum p_i^B = 1\right\} \tag{1}$$

where p_i^B is the probability of the action-target couple (a_i^B, t_i^B), which is defined as the action a_i^B to target t_i^B. Therefore, the decision space of Blue $A^1 = \times_{i\in R^B} D_i^B$. (Compared with the standard definition of Markov game model reviewed in the beginning part of Section 2.3.1, D_i^B is the action set of ith member of Blue team, which is deemed as a single player. So, generally, the meaning of A^1 is same as that of D^1 in the standard definition.) As an example, for the Blue small weapon UAV 1 in Blue team 1, its action might be d_1^B = {(attack, Red fighter 1, 0.3), (fly to, Red fighter 2, 0.5), (avoid, Red fighter 3, 0.2)}.

Similarly, each Red cluster (obtained from the level-two data fusion) determines a probability distribution over all possible action-target combinations. Let D_i^R denote the decision space of the ith Red cluster. Each element d_i^R of D_i^R is defined as

$$d_i^R = \left\{(a_i^R, t_i^R, p_i^R) \mid a_i^R \in A^R, t_i^R \in O^R, 0 < p_i^R \leq 1, \sum p_i^R = 1\right\} \tag{2}$$

where p_i^R is the probability of action a_i^R to target t_i^R. Therefore, the decision space of Red force $A^2 = \times_{i\in R^R} D_i^R$. A possible action for Red platform 1 (Red fighter 1) is d_1^R = {(attack, small weapon UAV 1, 0.6), (move to, Blue solider 2, 0.2), (avoid, Blue solider 1, 0.2)}.

REMARK 2 Decision and action verbs are different concepts. A decision is a set of triplets with associated probabilities while an action verb is just a component of the triplet composed of resource, action verb and objective. All actions are included in A^1 for player 1 (Blue force) and A^2 for player 2 (Red force). All action verbs are enumerated in A^B for player 1 (Blue force) and A^R for player 2 (Red force).

The decisions of White objects are relatively simple. The main action type is movement. Let D_i^W denote the decision space of the ith White unit. Each element d_i^B of D_i^B is defined as

$$d_i^W = \left\{(a_i^W, t_i^W, p_i^W) \mid a_i^W \in A^W, t_i^W \in O^W, 0 < p_i^W \leq 1, \sum p_i^W = 1\right\} \tag{3}$$

where p_i^W is the probability of action a_i^W to target t_i^W.

Transition Rule—Due to the uncertainty properties of military environments, we assume that the states of the Markov game have inertia so that the decision makers have more chance in the pursuit of the objective from previous actions. We define an inertia factor vector for each player. Without loss of generality, we take the Blue force as an example, $\eta^B = (\eta_1^B, \eta_2^B, \ldots, \eta_{m_B}^B)^T$, where m_B is the number of the teams or clusters of Blue force, and $0 \leq \eta_j^B \leq 1$, $1 \leq j \leq m_B$. So, for the jth team of the Blue player, there is a probability of η_j^B to keep the current action-target couple and a probability of $(1-\eta_j^B)$ to use a new action composed of action-target couples.

There are two steps to calculate the probability distribution over the state space S, where s_k, s_{k+1} are states at time step k and $k+1$ respectively, and a_k^B, a_k^R and a_k^W are the decisions of Blue force, Red force, and White force, respectively, at time step k.

Step 1 With the consideration of a inertia factor vector η^B, we combine the current state with decisions of both players to obtain fused probability distributions over all possible action-target couples for the Red and Blue forces. To do this, we first decompose the current state into the action-target couples for each team of each player (Red force, Blue force, or White force). Let $\Psi_j^B(s_k)$ denote the resulting action-target couple related to the jth team of the Blue player. For example, if there is one triplet of (Blue team 1, attack, Red fighter 2) in the current state s_k, then the action-target couple for Blue team 1 (the first team of Blue force) is $\Psi_1^B(s_k)$ = (attack, Red fighter 2). Secondly, for each specified team, say the jth cluster of Blue player 2 (Blue force), we fuse its action-target couples via modifying the probability of each possible action-target couple based on the following formula

$$\bar{p}^B((a_j^B, t_j^B) \mid s_k) = \begin{cases} p_j^B(1-\eta_j^B), & \text{if } (a_j^B, t_j^B, p_j^B) \in d_j^B \text{ and } (a_j^B, t_j^B) \notin \{\Psi_j^B(s_k)\} \\ p_j^B(1-\eta_j^B) + \eta_j^B, & \text{if } (a_j^B, t_j^B, p_j^B) \in d_j^B \text{ and } (a_j^B, t_j^B) \in \{\Psi_j^B(s_k)\} \\ \eta_j^B, & \text{if } (a_j^B, t_j^B, p_j^B) \notin d_j^B \text{ and } (a_j^B, t_j^B) \in \{\Psi_j^B(s_k)\} \\ 0, & \text{if } (a_j^B, t_j^B, p_j^B) \notin d_j^B \text{ and } (a_j^B, t_j^B) \notin \{\Psi_j^B(s_k)\} \end{cases}. \tag{4}$$

There are four cases in Eq (4): 1) The action-target couple (a_j^B, t_j^B) only occurs in the current action of the jth cluster of the Blue player and is not in the current state s_k, which can be mathematically represented by $(a_j^B, t_j^B, p_j^B) \in d_j^B$ and $(a_j^B, t_j^B) \notin \{\Psi_j^B(s_k)\}$. Then we know the probability of (a_j^B, t_j^B) in current state s_k is 0 and probability of (a_j^B, t_j^B) in current action is p_j^B. So, according to the definition of inertia, the fused probability of the action-target couple (a_j^B, t_j^B) is $p_j^B(1-\eta_j^B) + 0(\eta_j^B) =$

$p_j^B(1-\eta_j^B)$. 2) The action-target couple (a_j^B, t_j^B) happens both in the current action of the jth cluster of the Blue player and in the current state s_k. Then we know the probability of (a_j^B, t_j^B) in the current state s_k is 1 and probability of (a_j^B, t_j^B) in the current action is p_j^B. So, according to the definition of inertia, the fused probability of the action-target couple (a_j^B, t_j^B) is $p_j^B(1-\eta_j^B) + 1(\eta_j^B) = p_j^B(1-\eta_j^B) + \eta_j^B$. 3) The action-target couple (a_j^B, t_j^B) only occurs in the current state s_k, and then we know the probability of (a_j^B, t_j^B) in current state s_k is 1 and probability of (a_j^B, t_j^B) in the current action is 0. So, according to the definition of inertia, the fused probability of the action-target couple (a_j^B, t_j^B) is $0(1-\eta_j^B) + 1(\eta_j^B) = \eta_j^B$. 4) The action-target couple (a_j^B, t_j^B) occurs neither in the current state s_k nor in the current action of the jth cluster of the Blue player, and then we know the probability of (a_j^B, t_j^B) in the current state s_k is 0 and probability of (a_j^B, t_j^B) in the current action is 0. So, according to the definition of inertia, the fused probability of the action-target couple (a_j^B, t_j^B) is $0(1-\eta_j^B) + 0(\eta_j^B) = 0$.

Similarly, the new probability distribution for the jth team of the Red player (Red force) is

$$\bar{p}^R((a_j^R, t_j^R) \mid s_k) = \begin{cases} p_j^R(1-\eta_j^R), & \text{if} \quad (a_j^R, t_j^R, p_j^R) \in d_j^R \\ & \text{and} \quad (a_j^R, t_j^R) \notin \Psi_j^R(s_k) \\ p_j^R(1-\eta_j^R) + \eta_j^R, & \text{if} \quad (a_j^R, t_j^R, p_j^R) \in d_j^R \\ & \text{and} \quad (a_j^R, t_j^R) \in \Psi_j^R(s_k) \\ \eta_j^R, & \text{if} \quad (a_j^R, t_j^R, p_j^R) \notin d_j^R \\ & \text{and} \quad (a_j^R, t_j^R) \in \Psi_j^R(s_k) \\ 0, & \text{if} \quad (a_j^R, t_j^R, p_j^R) \notin d_j^R \\ & \text{and} \quad p(a_j^R, t_j^R) \notin \Psi_j^R(s_k) \end{cases} . \tag{5}$$

The new probability distribution for jth team of White player (White force) is

$$\bar{p}^W((a_j^W, t_j^W) \mid s_k) = \begin{cases} p_j^W(1-\eta_j^W), & \text{if} \quad (a_j^W, t_j^W, p_j^W) \in d_j^W \\ & \text{and} \quad (a_j^W, t_j^W) \notin \{\Psi_j^W(s_k)\} \\ p_j^W(1-\eta_j^W) + \eta_j^W, & \text{if} \quad (a_j^W, t_j^W, p_j^W) \in d_j^W \\ & \text{and} \quad (a_j^W, t_j^W) \in \{\Psi_j^W(s_k)\} \\ \eta_j^W, & \text{if} \quad (a_j^W, t_j^W, p_j^W) \notin d_j^W \\ & \text{and} \quad (a_j^W, t_j^W) \in \{\Psi_j^W(s_k)\} \\ 0, & \text{if} \quad (a_j^W, t_j^W, p_j^W) \notin d_j^W \\ & \text{and} \quad (a_j^W, t_j^W) \notin \{\Psi_j^W(s_k)\} \end{cases} . \tag{6}$$

Step 2 We determine the probability distribution over the all possible outcomes of state s_{k+1},

$$q(s_{k+1} \mid s_k, a_k^B, a_k^R, a_k^W) = \prod_{j=1}^{m_B} \bar{p}^B((a_j^B, t_j^B) \mid s_k) \prod_{j=1}^{m_R} \bar{p}^R((a_j^R, t_j^R) \mid s_k) \times \prod_{j=1}^{m_W} \bar{p}^W((a_j^W, t_j^W) \mid s_k) \tag{7}$$

when

$$s_{k+1} = \bigcup_{j=1}^{m_B} \{(r_j^B, a_j^B, t_j^B)\} \bigcup_{j=1}^{m_R} \{(r_j^R, a_j^R, t_j^R)\} \bigcup_{j=1}^{m_W} \{(r_j^W, a_j^W, t_j^W)\},$$

otherwise, $q(s_{k+1} \mid s_k, a_k^B, a_k^R, a_k^W) = 0$. Where m_B is the number of the teams or clusters of the Blue player (Blue force), m_R is the number of the teams or groups of the Red player (Red force) and m_W is the number of the units of the White player (White force). $\{(r_i^B, a_i^B, t_i^B)\}$ is the set of all possible (with positive probability) triplets for the ith team of the Blue player. Therefore $\bigcup_{i=1}^{m_B} \{(r_i^B, a_i^B, t_i^B)\}$ contains all the possible (with positive probability) triplets for the Blue force. From step 1, we know that the fused probability of each specified (a_j^B, t_j^B) is $\bar{p}^B((a_j^B, t_j^B) \mid s_k)$ defined in equation (1). With the assumption that all teams of Blue force are independent, we obtain the overall probability of Blue force, $\prod_{j=1}^{m_B} \bar{p}^B((a_j^B, t_j^B) \mid s_k)$. Similarly, $\prod_{j=1}^{m_R} \bar{p}^R((a_j^R, t_j^R) \mid s_k)$ and $\prod_{j=1}^{m_R} \bar{p}^W((a_j^W, t_j^W) \mid s_k)$ are the overall probabilities of the Red and White force, respectively. So the probability distribution over the all possible outcomes of state s_{k+1} (composed of all possible sub-states of Blue, Red, and White force) can be calculated via equation (7).

Payoff Functions—In our proposed decentralized Markov game model, there are two levels of payoff function for each player (Blue, Red or White).

The lower (local) level payoff functions are used by each team or cluster to determine the team actions based on the local information. For the jth team of Blue force, the payoff function is defined as $f_j^B(\tilde{s}_j^B, d_j^B, W_k^B)$, where $\tilde{s}_j^B \subseteq s$ is the local information (note that in a distributed and partial observable framework, local information for each player means the battle or state information is available to the player.) obtained by the team, and W_k^B, the weights for all possible action-target couples of Blue force, is announced to all Blue teams and determined according the top level payoff functions by the supervisor of Blue force.

$$f_j^B(\tilde{s}_j^B, d_j^B, W_k^B) = \sum_{(a_i^B, t_i^B, p_i^B) \in d_j^B} w^B(j, a_i^B, t_i^B, W_k^B) p_i^B g^B(j, a_i^B, t_i^B, \tilde{s}_j^B) \tag{8}$$

where, $w^B(j,a_i^B,t_i^B,W_k^B)$ will calculate the weigh for any specified action-target couple for the jth team of Blue force from the W_k^B, p_i^B is the probability of the action-target couple (a_i^B,t_i^B), and $g^B(j,a_i^B,t_i^B,\tilde{s}_j^B)$ will determine the gain from the action-target couple (a_i^B,t_i^B) for the jth team of Blue force according to the positions and features, such as platform values and defense/offense capability, of the Blue and Red platforms. Similarly, we obtain the lower level payoff functions for the jth team of Red or enemy force,

$$f_j^R(\tilde{s}_j^R,d_j^R,W_k^R) = \sum_{(a_i^R,t_i^R,p_i^R)\in d_j^R} w^R(j,a_i^R,t_i^R,W_k^R)p_i^R g^R(j,a_i^R,t_i^R,\tilde{s}_j^R) \tag{9}$$

$$f_j^W(\tilde{s}_j^W,d_j^W,W_k^W) = \sum_{(a_i^W,t_i^W,p_i^W)\in d_j^W} w^W(j,a_i^W,t_i^W,W_k^W)p_i^W g^W(j,a_i^W,t_i^W,\tilde{s}^W). \tag{10}$$

REMARK 3 For some asymmetric threats, such as suicide bombers, the payoff functions may only consider the loss of the Blue side. For some camouflage and concealment entities, their objectives are to hide themselves and move close to the Blue units. Other deception units will do some irrational and additional movements to hide their true goals.

REMARK 4 People usually think of a military conflict situation as a zero-sum game—a game with a winner and a loser. In zero-sum game theory, the players have opposite objectives. If one player maximizes an objective function, the other automatically minimizes it. This is equivalent to a player maximizing an objective function and the other player maximizing the negative of the same function. Since the sum of the objective functions is zero, the game is called a zero-sum game. But when there are significant differences between the cultures of the Red and Blue forces and significant differences in the valuations of their assets and their opponent's assets, the zero-sum game approach in general is not representative. For example, a Blue objective might be to preserve as much of the Blue assets and to destroy as much of the Red assets as possible. However, recent experience with terrorist type battles suggests that the Red force may not be as concerned as the Blue force with preserving its own assets. The objectives in such a situation are not opposite of each other and a nonzero-sum approach would be much more appropriate.

The top (global) level payoff functions are used to evaluate the overall performance of each player.

$$J^B = \sum_k \left[\sum_{j=1}^{m_B} f_j^B(\tilde{s}_j^B,d_j^B,W_k^B)\right] \tag{11}$$

$$J^R = \sum_k \left[\sum_{j=1}^{m_R} f_j^R(\tilde{s}_j^R,d_j^R,W_k^R)\right] \tag{12}$$

$$J^W = \sum_k \left[\sum_{j=1}^{m_W} f_j^W(\tilde{s}_j^W,d_j^W,W_k^W)\right] \tag{13}$$

where k is the time index. In our approach, the calculation of the lower level payoffs are distributed and sent back to commander/supervisor via communication networks.

REMARK 5 Since the gain functions $g^B(j,a_i^B,t_i^B,\tilde{s}_j^B)$ for Blue force, $g^R(j,a_i^R,t_i^R,\tilde{s}_j^R)$ for Red force and $g^W(j,a_i^W,t_i^W,\tilde{s}_j^W)$ for White force are different functions, asymmetric force and cost utilities can be straightforwardly represented in our model. In addition, after an irregular adversary is detected, a different type of gain function will be assigned dynamically.

REMARK 6 In our Markov game model, the states used in the control strategies are the estimates of the future systems states. These estimates will evaluate or update following the Markov decision process 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.

Strategies—In this project, we have tried several well known types of strategies. Here we only give a brief description about three of them:

Pure Nash Strategies with a finite horizon. In game theory, the Nash equilibrium (named after John Nash [17] who proposed it) is a kind of optimal collective strategy in a game involving two or more players, where no player has anything to gain by changing only his or her own strategy. If each player has chosen a strategy and no player can benefit by changing his or her strategy while the other players keep their's unchanged, then the current set of strategy choices and the corresponding payoffs constitute a Nash equilibrium. In our approach, we use a game search tree to find the solution.

Mixed Nash Strategies. A mixed strategy is used in game theory to describe a strategy comprised of possible actions and an associated probability, which corresponds to how frequently the action is chosen. Mixed strategy Nash equilibria are equilibria where at least one player is playing a mixed strategy. Nash proved that that every finite game has Nash equilibria but not all have a pure strategy Nash equilibrium.

Correlated Equilibria [26]. Unlike Nash equilibria, which are the concept of equilibria formulated in independent strategies, correlated equilibria were developed from correlated strategies in non-cooperative games. The correlated equilibrium of a Markov game describes a solution for playing a dynamic game in which players are able to communicate but are self-interested. Based on the signals, which are generated by the correlated devices and announced to each decision maker, players choose their actions according to the received private signals. There are two types of correlation devices: autonomous and stationary devices. An autonomous correlation device is a pair $\mathcal{D} = (((M_n^i)_{i\in N}, d_n)_{n\in N})$, where (i) M_n^i is a finite set of signals for player i at time step n, and (ii) $d_n : M(n) \rightarrow \Delta(M_n)$, $M_n = \times_{i\in N} M_n^i$ and $M(n) = M_1 \times M_2 \times \cdots \times M_{n-1}$. A stationary correlation device is a pair $\mathcal{D} = (((M^i)_{i\in N}, d))$, where $d \in \Delta(M)$ and $M = \times_{i\in N} M^i$. Actually, a stationary correlation device is a special case of an autonomous correlation device, where M_n^i is independent of n and d_n is a constant function that is independent of n.

Given a correlation device $\mathcal{D}$, we define an extended game $G(\mathcal{D})$. The game $G(\mathcal{D})$ is played exactly as the original game, but at the beginning of each stage n, a signal combination $m_n = (m_n^i)_{i\in N}$ is drawn according to the probability function $d_n(m_1, m_2, \ldots, m_{n-1})$ and each player i is informed of m_n^i. Then each decision maker must base his choice of actions on the received signal. Any deviator will be punished via his min-max value. The punishment only occurs if a player disobeys the recommendation of the device. Every Markov game with an autonomous correlated device admits a correlated equilibrium [26].

REMARK 7 In our proposed approach, the solution to the Markov game model is obtained via a K time-step look-ahead approach, in which we only optimize the solution in the K time-step horizon. We set K as 5 during the simulations of the Section 3—Experiments. Actually, this suboptimal technique is used successfully for calculations in games such as chess, backgammon, and monopoly.

2.3.2. Hierarchical Task Network

Once the ECOA hypotheses have been generated, they must be evaluated. However, since the generated hypotheses are not directly observable, they are not suitable for correctness testing. As with any hypothesis test, observables must be identified. These observables act as indicators to refute or support ECOA hypotheses. A Hierarchical Task Network (HTN) planner [11] is employed to decompose ECOA hypotheses into observable task sequences.

A construct known as the Hierarchical Task Network (HTN) provides a representation of tasks at various levels of specificity. The HTN not only mimics the variation in specificity found in military echelons, it also allows a computational construct for analyzing ECOAs. In our game theoretic approach to level-three fusion (threat assessment), the HTN is employed to provide a method for decomposing high-level ECOAs into more specific tasks. The HTN representation is the basis of most modern planning algorithms. It is based on the concept that humans plan by decomposing tasks into smaller ones until a sequence of tractable tasks are found that satisfy the objective [7]. These are tasks that the fusion processes attempt to infer or observe directly and are assumed to be tractable.

3. EXPERIMENTS

In the simulation part, we build a virtual battle-space and a typical urban scenario based on the ontology concept, which is an explicit, formal, machine-readable semantic model that defines the classes (or concepts) and their possible inter-relations specific to some specified domain. To simulate our data fusion approach, we implemented and tested our battle-space, scenario and algorithms on our prototype software with developed and funded cooperative path planning and mission planning algorithms [8], [9], [24].

3.1. Scenario Description

We used a scenario shown in Fig. 3 to demonstrate the performance of our proposed threat prediction and situation awareness algorithm. In the shown urban environment, the Blue force's missions are to capture two bridges and to do security patrol on the main roads connecting the two bridges. The Blue ground force consists of 3 teams of three soldiers each with sniper rifles. The Red force includes 3 armed fighters and 3 asymmetric adversaries hiding in and acting like the White objects (the civilians and vehicles). We assume there is an asymmetry in total forces between Blue side and Red side. Blue has more soldiers than Red. Moreover, the objectives of Blue side and Red side are asymmetric: the objectives of Red side are to kill Blue forces without considering the loss of themselves and the consideration of collateral damage. The main challenge for both sides is to understand the situation from the fused sensor data and predict the intent of the opponent under the "believed" war situation.

REMARK 8 In this scenario, the kill probability (of each weapon type) and the target value of each unit (Blue, Red, and White force) are pre-specified.

3.2. Implementation

To demonstrate our approach, we developed simulation software (Fig. 4) as a controller module for the MICA (Mixed Initiative Control of Automa-Teams) Open Experimental Platform (OEP) [28].

For the scenario (Fig. 3), the possible actions for blue side are "Blue Team 1 move to Bridge 1," "Blue Team 2 Attack Red Fighter 2," or "Blue Team 3 Halt." In general, R^B = {Blue Team 1, Blue Team 2, Blue Team 3}, A^B = {Move to, Attack, Halt}, and O^B = {Red Fighter 1, Red Fighter 2, Red Fighter 3, Bridge 1, Bridge 2, Dummy, Detected Asymmetric Threats}. The possible actions for red force are "Fighter 1 attack Blue team 1," "Asymmetric threat acts as a civilian." In general, R^R = {Fighter 1, Fighter 2, Fighter 3, Asymmetric threat}, A^R = {Move to, Attack, Act as a civilian, Halt}, and O^R = {Blue team 1, Blue team 2, Blue team

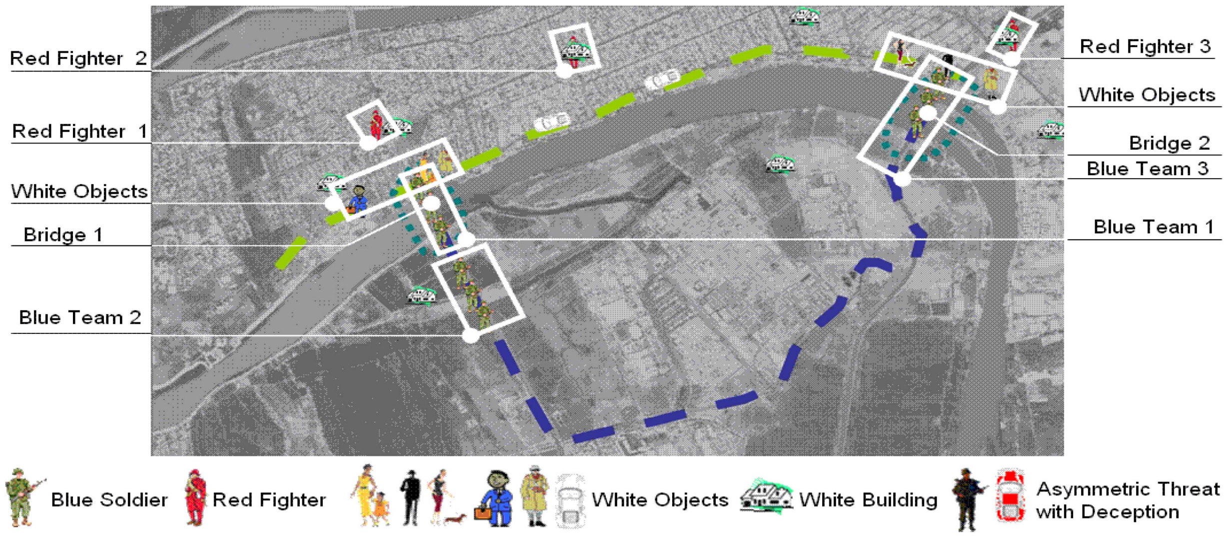

Fig. 3. A simulated scenario—urban warfare for combating guerrilla forces.

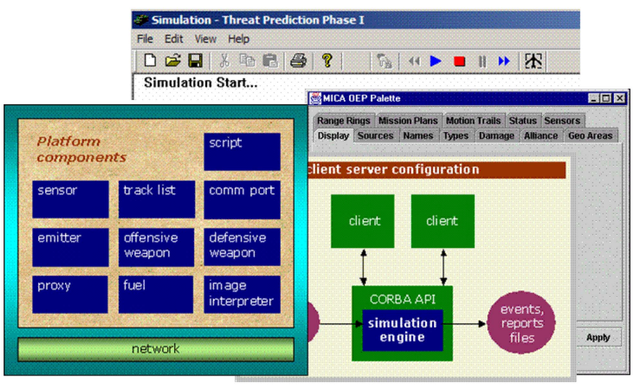

Fig. 4. Simulation Software—a controller module for MICA OEP virtual battlespace.

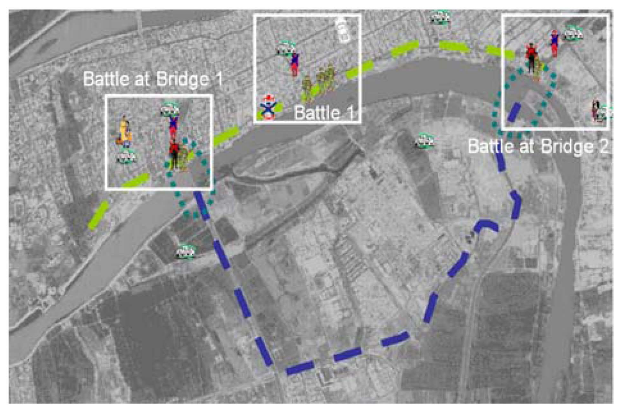

Fig. 5. Result of a simulation run.

3, Bridge 1, Bridge 2, Dummy}. The actions for White side include "Civilian 1 move to safe place," "Civilian 2 move to Bridge 1," and "Civilian 3 move to dangerous place." Mathematically, R^W = {Civilian 1, Civilian 2,...}, A^W = {Move to, Halt}, and O^R = {Bridge 1, Bridge 2, Dummy, Safe place, Dangerous place}.

In this simulation we set all inertia values to 0.1 and we also assume that the there is no measurement error for the Blue, Red, and White forces.

The objective of the Blue force is to save Bridge 1, Bridge 2, Blue teams, and Civilians; and eliminate Red Fighter 1, Red Fighter 2, Red Fighter 3 and possible asymmetric threats. The goal of the Red side is to Destroy Bridge and Kill Blue teams (we assume that Red force has to kill Blue teams nearby before destroying Bridge 1 or 2). The White force's goal is to protect civilians. Each side will estimate the information of damage status (probability and expectation value) and calculate its cost function based on the unit values: Bridge (100), Blue team (50), Red Fighter (20), Asymmetric threat (50), Civilian (0 for "don't care about collateral damage" or 10 for "care about collateral damage"). We set the kill probability to 0.5.

To solve the Markov game problem, we have conducted a numerical procedure to compute the strategies with a 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 the other players) and several one-step static matrix games (one game for each player at every current system state). Then existing algorithms (MDP MATLAB toolbox and Gambit [29]) will be exploited to solve the MDPs and matrix games.

3.3. Experiments

For the scenario, in a specific simulation run (Markov game approach with correlated equilibrium) as shown in Fig. 5, Blue team 1 and Blue team 3 were assigned to secure Bridge 1 and Bridge 2, respectively, almost for the whole simulation period of 30 minutes. Blue team with 3 Blue soldiers was doing security patrol on the two major roads connecting two bridges and

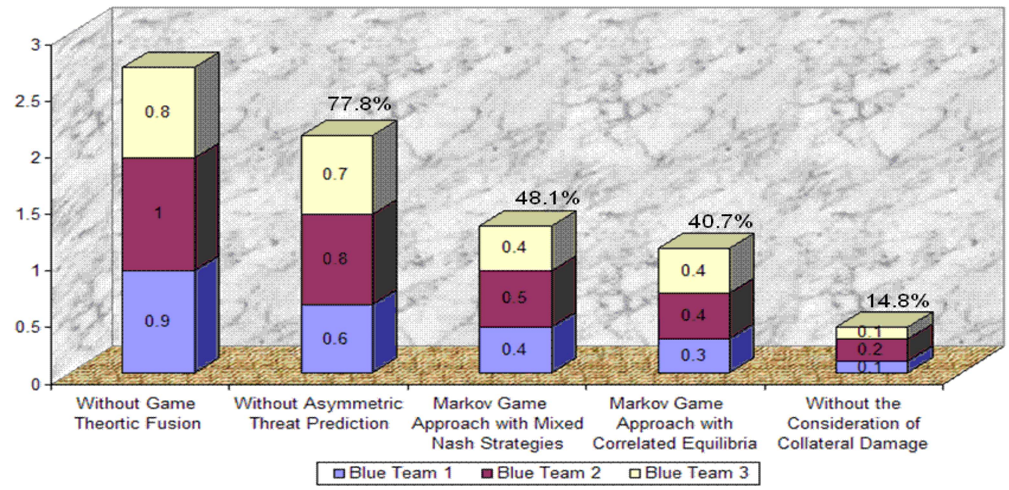

Fig. 6. Damage comparison of various options.

some important areas. On the other hand, Red fighters and asymmetric adversaries are trying their best to kill Blue forces. The first battle happened when Red Fighter 2 tried to attack Blue Team 2 with the help of an asymmetric White vehicle with deception (hiding in White vehicles). During this period, one asymmetric adversary vehicle, which posed civic activities at first and carried out abnormal activities during the battle, is detected and killed. Without the help of the Red vehicle, Red fighter 2 was killed by Blue team 2. Almost at the same time, the asymmetric adversaries near Bridge 1 and Bridge 2 were attacking the Blue team 1 and 2. At this stage, two civilians were detected and killed as asymmetric adversaries. Without the help from the asymmetric adversaries with deception, Red fighter 1 and 3 were killed by Blue team 1 and 3 at Bridges 1 and 2, respectively. In this specific run, there is no loss of Blue soldiers since our algorithm predicted the intents of the Red side correctly and promptly.

In addition to the explained run, we performed many experiments. We compared the results using the various options, such as without game theoretic fusion (without level-two or level-three fusion, and a Bayesian Network approach), without asymmetric-threat prediction (with level-two fusion but the payoff function of game model at level-three fusion doesn't change dynamically), game approach with mixed Nash strategy, game approach with correlated equilibria, and the game approach without collateral damage consideration in the cost function of Blue side. Since the simulation is stochastic, the results consist of the mean of 10 runs for each case, which are shown in Fig. 6 (Only the damage information for the Blue side is shown). From the damage comparison results, we can see that our Markov game approach with correlated equilibrium and deception consideration for threat detection and situation awareness is better than the other methods except the game approach without collateral damage consideration.

4. CONCLUSIONS

Game theoretic tools have a potential for threat prediction that takes uncertainties in Red plans and deception possibilities into consideration. In this paper, we have evaluated the feasibility of the Markov game theoretic data fusion algorithm. The effectiveness has been demonstrated through extensive simulations. The scalability and stability analysis of our game theoretic approach is one direction of future research.

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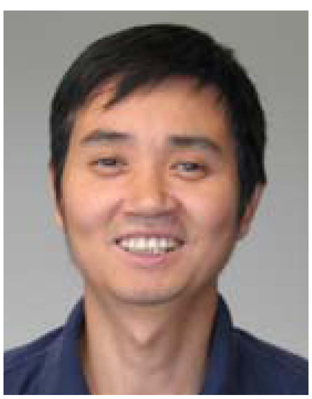

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Dr. Cruz was elected as a member of the National Academy of Engineering (NAE) in 1980. In 2003, he was elected a Corresponding Member of the National Academy of Science and Technology (Philippines). He is also a Fellow of the American Association for the Advancement of Science (AAAS), elected 1989, a Fellow of the American Society for Engineering Education (ASEE), elected in 2004, and a Fellow of International Federation of Automatic Control (IFAC), appointed 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, 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. Currently, he serves as Chair (2004–2005) of the Engineering Section of the American Association for the Advancement of Science (AAAS).

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Before coming to ONR, Mr. Kruger served as a research and development manager for the Future Theater Air and Missile Defense program office at the Naval Sea Systems Command. He has also worked for the Marine Corps Warfighting Laboratory and for the Naval Surface Warfare Center Indian Head Division. Mr. Kruger started his career as a Naval Officer, serving as an instructor at the Naval Nuclear Propulsion School.

After leaving active duty, Captain Martin Kruger has continued serving the Navy as a drilling reservist. Reserve assignments have included four command tours, one each at a shipyard, a SUPSHIP, a NAVSEA field activity and a Weapon Station. He is currently serving as a Chief Ordnance Inspector.

Martin Kruger holds Bachelor in engineering in Chemical Engineering, a Master of Science in Industrial Chemistry and a Masters in Business Administration. He is also a graduate of the Naval War College and is Level 3 Certified in Program Management.

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 Ph.D. 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 Major 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.