A Game Theoretic Approach to Threat Intent Inference

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The State of the Art and the State of the Practice

Outline

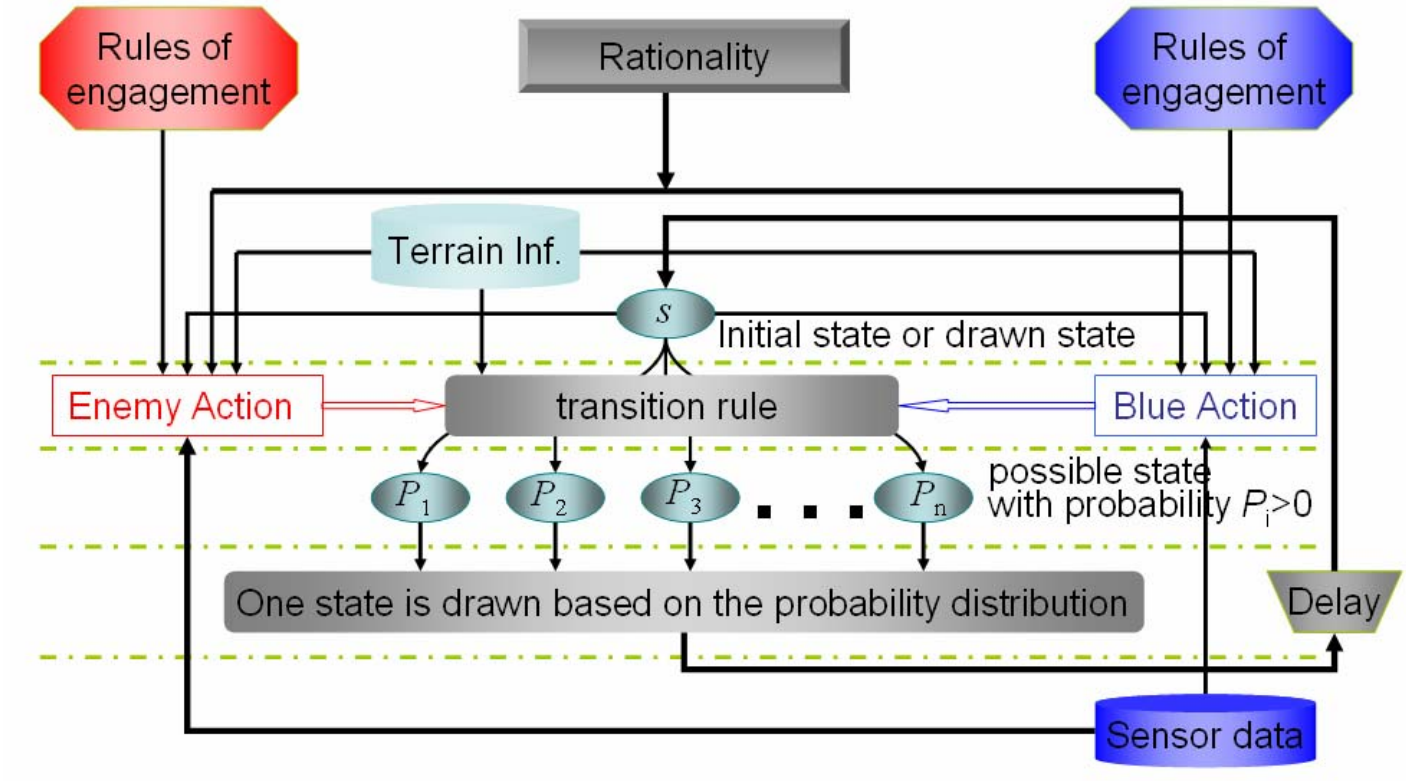
- Introduction
- Technical Approach
- Simulation and Experiments
- Conclusions

Introduction

- In the adversarial military environment, it is important to efficiently and promptly predict the enemy's or adversary tactical intent.
- Game theory provides a framework for modeling and analyzing various interactions between intelligent and rational decision makers, or players in conflict situations, in which every individual decision maker is not in complete control of other decision units.
- In this paper, the focus is on the application of Markov Game, the multi-agent extensions of Markov Decision Processes (MDPs), to the estimation of enemy course of actions (COAs), which approximately model the intent of targets.

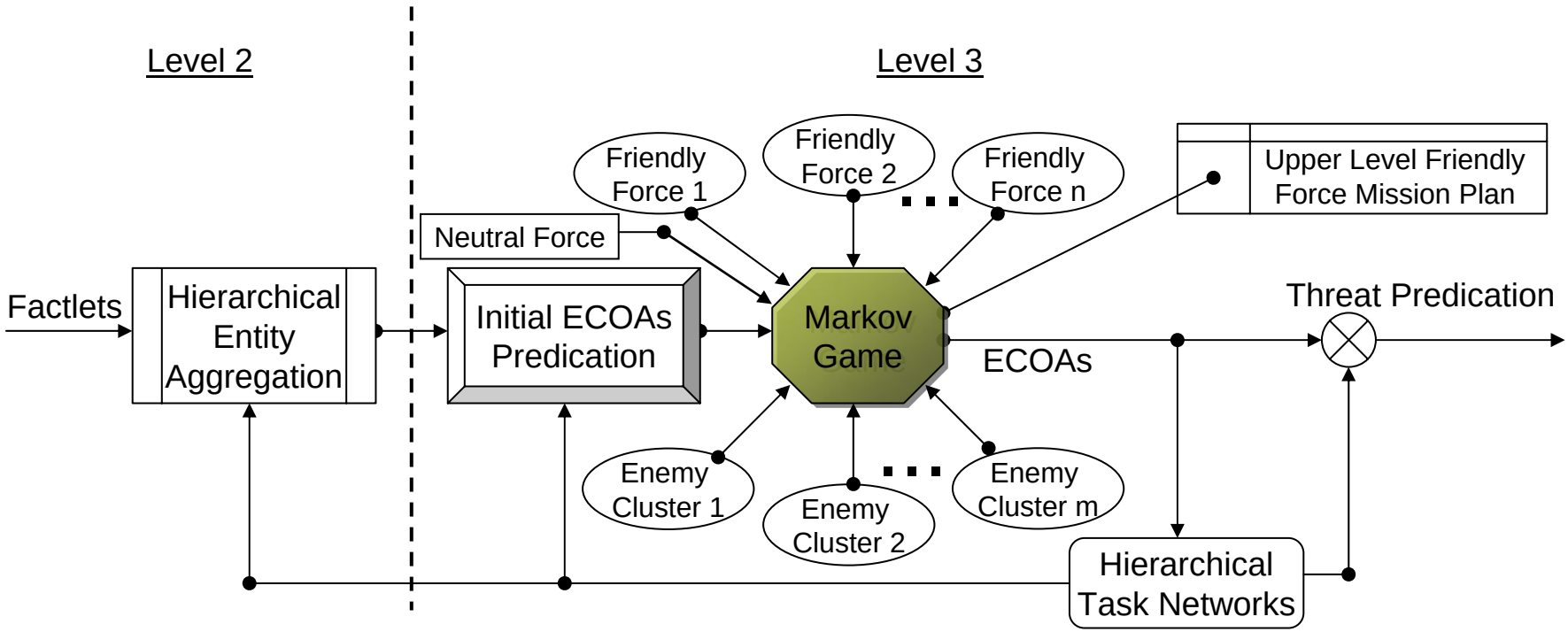
Algorithm Overview

- Overall Architecture:



Technical Approach

- A stochastic (Markov) game model



Technical Approach

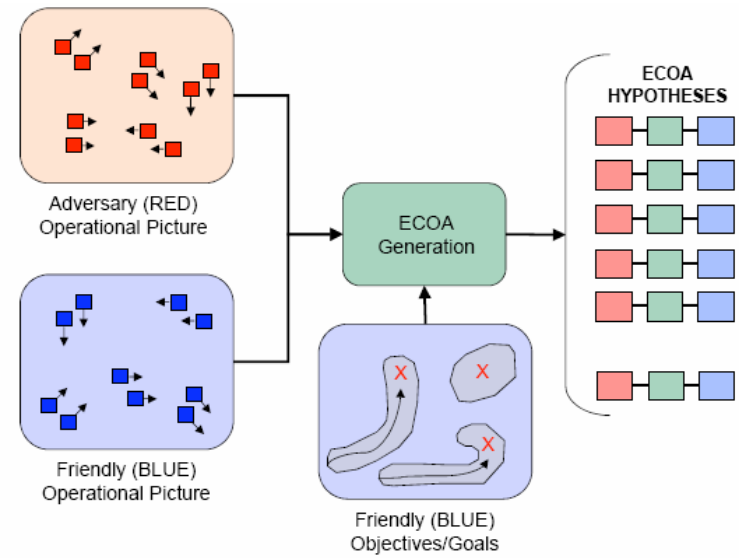
- A stochastic (Markov) game model
  - Decentralized Approach
  - Deception (Asymmetric Adversary)
  - Markov Decision Process
  - Game Theoretic Framework with
    - Red Player (Enemy Force)
    - White Player (Neutral Force)
    - Blue Player (Friendly Force)
  - Dynamic Strategy Adjustment

Technical Approach

- A stochastic (Markov) game model
  - Advantages:
    - Decentralized. Each cluster or team makes decisions mostly based on the local information. We put more autonomies in each group allowing for more flexibilities
    - Markov Decision Process (DMP) can effectively model the uncertainties in the noisy military environment.
    - Game framework is an effective and ideal model to capture the nature of military conflicts: the determination of one side's strategies is tightly coupled to that of the other side's strategies and vice versa.

Technical Approach

- ECOAs Prediction
  - The procedure to generate ECOA hypotheses is similar to the process of Track Initiation in Level 1 Fusion, where measurements are used to initiate a new track when they do not associate with any existing tracks



Definition

- A Markov (stochastic) game is given by (i) a finite set of players N, (ii) a finite set of states S, (iii) for very player $i \in N$, a finite set of available actions D^i, and the overall action space $D = \times_{i \in N} D^i$, (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:

Technical Approach

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

Technical Approach

- State Space
  - All the possible Course of Actions (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)

Technical Approach

- State Space
  - We define state $s = (s^B, s^R, s^W)$ and state space $S = S^B \times S^R \times S^W$, where $s^B \in S^B$ is the COAs of Blue (friendly) force

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

    , and R^B, A^B, 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 $s^W \in S^W$ for white player (neutral force)

Technical Approach

- Action Space
  - At every time step, each player choose a list of targets with associated actions and confidences based on its local battle field information, such as the unit type and positions of possible targets.
  - Let D_i^B denote the action space of the ith blue team. Each element d_i^B of D_i^B is defined as

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

where p_i^B is the probability of the action-target couple (a_i^B, t_i^B), which defined as the action a_i^B to target t_i^B

Technical Approach

- Action Space
  - The action space of blue side $A^1 = \times_{i \in R^B} D_i^B$
  - As an example, for the blue small weapon UAV 1 in blue team 1, its action might be ={(attack, red fighter 1, 0.3), (fly to, red fighter 2, 0.5), (avoid, red fighter 3, 0.2)}.
  - Similarly, Let D_i^R denote the action space of the ith red cluster. Each element d_i^R of D_i^R is defined as

$$d_i^R = \{(a_i^R, t_i^R, p_i^R) \mid a_i^R \in A^R, t_i^R \in O^R, 0 < p_i^R \le 1, \sum p_i^R = 1\}$$

  - Therefore, the action space of red force is $A^2 = \times_{i \in R^R} D_i^R$

Technical Approach

- 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 pursuit of the objective of the previous action.
  - We define an inertia factor vector $\eta^i = (\eta_1^i, \eta_2^i, \cdots, \eta_{m_i}^i)^T$ for player i, where m_i is the number of the teams or clusters of player i , and $0 \le \eta_j^i \le 1$, $1 \le j \le m_i$
  - So, for the jth team of the player i, there is a probability of η_j^i to keep the current action-target couple and a probability of (1- η_j^i) to use the new action, which is composed of action-target couples.

Technical Approach

- Transition rule
  - There are two steps to calculate the probability distribution over the state space, $q(s_{k+1} \mid s_k, a_k^1, a_k^2)$, where s_k, s_{k+1} are states of time step *k* and *k*+1 respectively, a_k^1, a_k^2 are the decisions of player 1 (blue force or friendly force) and player 2 (red force or enemy), respectively, at time step *k*.
    - Step 1: we combine the current state with decisions of both players to obtain fused probability distributions over all possible action-target couples for red and blue forces.

$$\bar{p}\left((a_j^R, t_j^R) \mid s_k\right) = \begin{cases} p_j^R(1-\eta_j^2) & , \quad (a_j^R, t_j^R, p_j^R) \in d_j^R \ \ and \ \ (a_j^R, t_j^R) \notin \Psi_j^2(s_k) \\ p_j^R(1-\eta_j^2) + \eta_j^2 & , \quad (a_j^R, t_j^R, p_j^R) \in d_j^R \ \ and \ \ (a_j^R, t_j^R) \in \Psi_j^2(s_k) \\ \eta_j^2 & , \quad (a_j^R, t_j^R, p_j^R) \notin d_j^R \ \ and \ \ (a_j^R, t_j^R) \in \Psi_j^2(s_k) \\ 0 & , \quad (a_j^R, t_j^R, p_j^R) \notin d_j^R \ \ and \ \ (a_j^R, t_j^R) \notin \Psi_j^2(s_k) \end{cases}$$

Technical Approach

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

$$q(s_{k+1} \mid s_k, a_k^1, a_k^2) =$$

$$\begin{cases} \prod_{i=1}^{m_1} \overline{p}\left((a_i^B, t_i^B) \mid s_k\right) \prod_{j=1}^{m_2} \overline{p}\left((a_j^R, t_j^R) \mid s_k\right) & , \quad s_{k+1} = \bigcup_{i=1}^{m_1} \{(r_i^B, a_i^B, t_i^B)\} \bigcup_{j=1}^{m_2} \{(r_j^R, a_j^R, t_j^R)\} \\ 0 & , \quad otherwise \end{cases}$$

.

where $\Psi_j^i(s_k)$ denote the decomposed action-target couple of the jth team of the ith player from the current state s_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 level payoff functions are used by each team or cluster to determine the team actions based on the local information

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

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

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

where $\tilde{s}_j^B \subseteq s$ is a subset of the state s. $\tilde{s}_j^B$ represents the local information obtained by the jth team of the blue force

Technical Approach

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

$$J^B = \sum_k \left[\sum_{j=1}^{m_1} f_j^B(\tilde{s}_j^B, d_j^B, W_k^B) \right]$$

$$J^R = \sum_k \left[\sum_{j=1}^{m_2} f_j^R(\tilde{s}_j^R, d_j^R, W_k^R) \right]$$

$$J^W = \sum_k \left[\sum_{j=1}^{m_3} f_j^W(\tilde{s}_j^W, d_j^W, W_k^W) \right]$$

- In our approach, the lower lever payoffs are calculated distributedly and sent back to commander/supervisor via communication networks.

Technical Approach

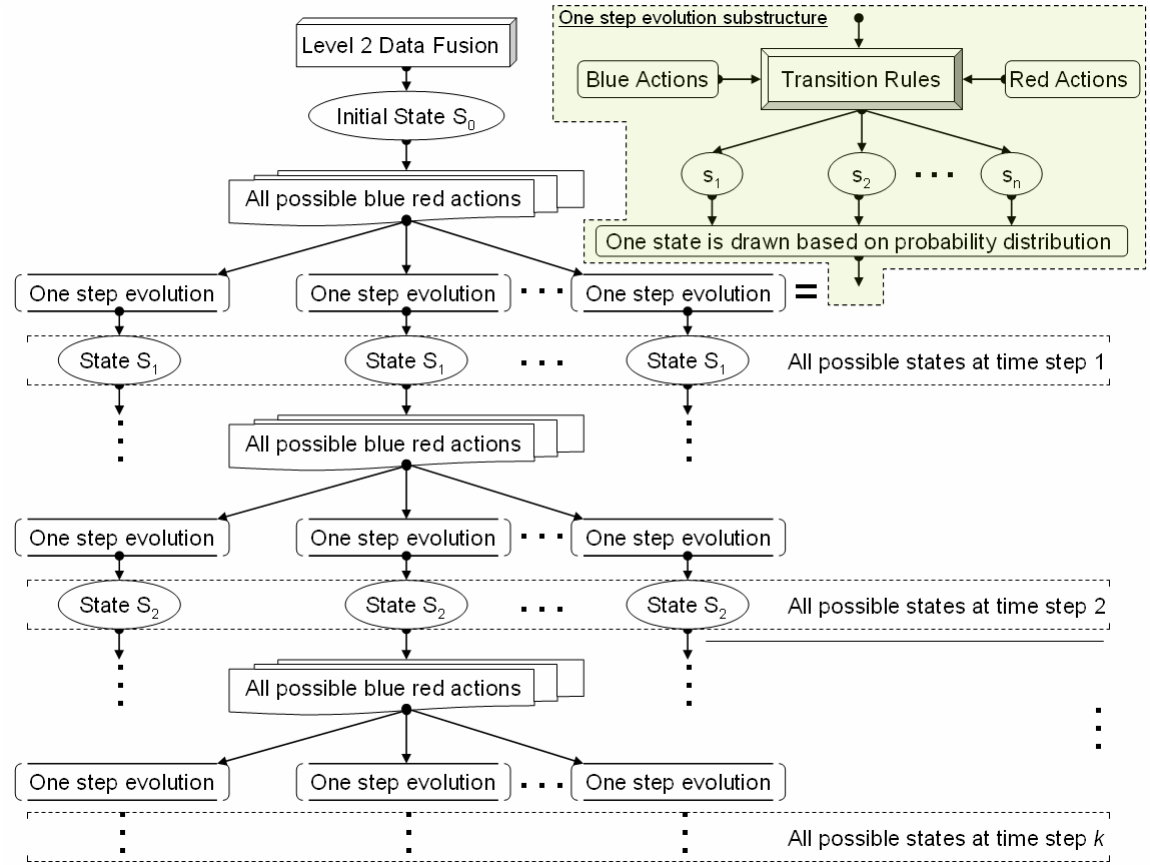
- The strategies
  - Min-max strategies. This kind of strategies will give a conservative solution to minimize the possible maximum “loss”
  - Leader-Follower Strategies. With the consideration of the limited and non-perfect communication, we use the Stackelberg conception to model the cooperation part between the commander and the local teams.
  - Pure Nash Strategies.

$$J_B(\pi^*, \phi^*) \geq J_B(\pi, \phi^*)$$

$$J_R(\pi^*, \phi^*) \geq J_R(\pi^*, \phi)$$

Technical Approach

- We use a game tree to find the finite horizon Nash solution



Technical Approach

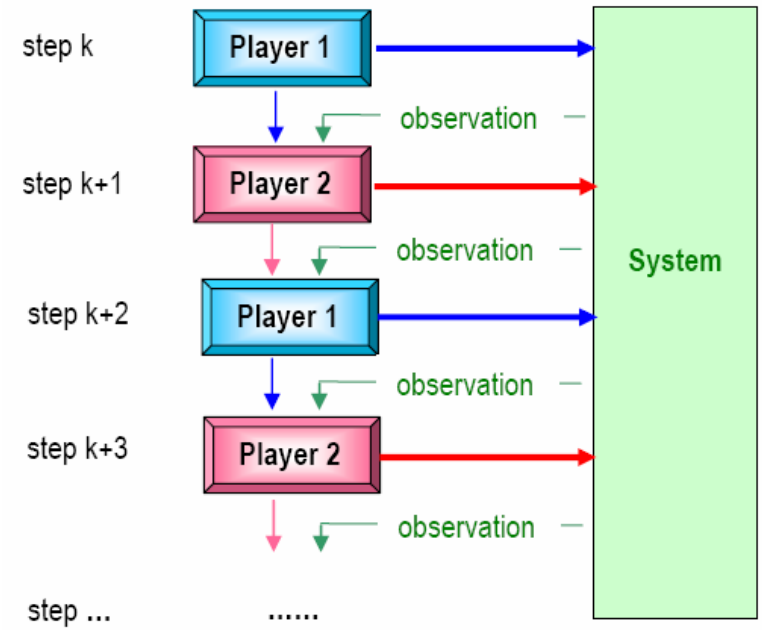
- In our proposed approach, the solution to the Markov game tree is obtained via a *K* time-step look-ahead approach, in which we only optimize the solution in the *K* time-step horizon. *K* usually takes 2, 3, 4, or 5. The suboptimal technique is used successfully for reasoning in games such as chess, backgammon and monopoly
- 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. It was proved by Nash that that every finite game has Nash equilibria but not all has a pure strategy Nash equilibrium.

Technical Approach

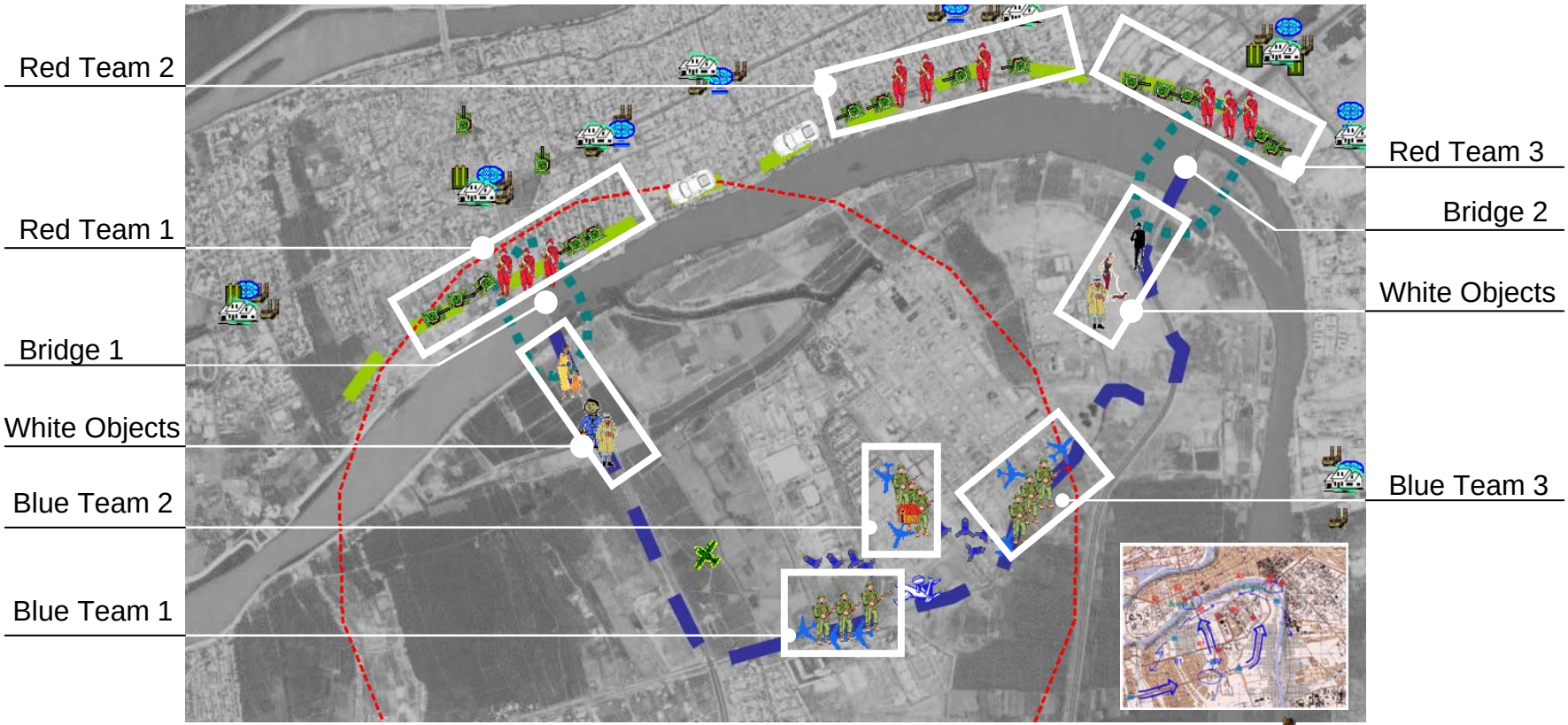
- Correlated Equilibria. Unlike Nash equilibria, which are the concept of equilibria formulated in independent strategies, the correlated equilibria were developed from the correlated strategies in non-cooperative games.
- The correlated equilibrium of a Markov game describes a solution for playing a dynamic game in which players are able to communicate but are self-interested.
- Based on the signals generated by the correlated devices and announce to the each decision maker, players choose their actions according to the received private signals.
- It was proved that every Markov game with an autonomous correlated device admits a correlated equilibrium.

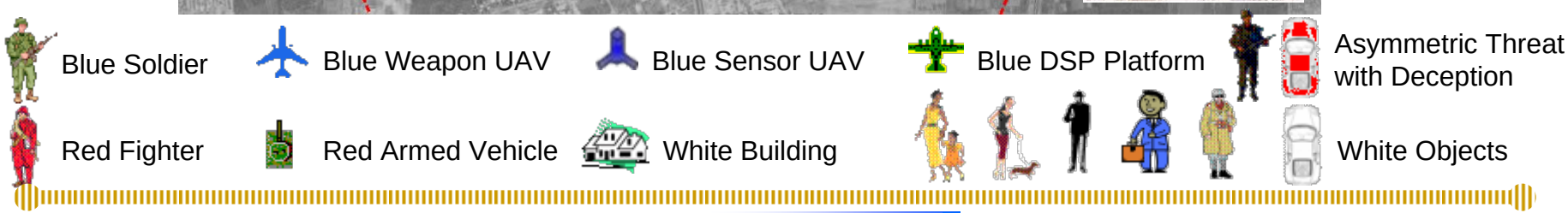
Technical Approach

- Sequential Nash Strategies. A sequential game is one in which players choose their strategies following a certain predefined order, and in which at least some players can observe the moves of other players who make decisions preceded them
- In our approach, we use a turn-by-turn scheme shown in the following figure



Simulation and Experiments





To capture two bridges which are guarded by the enemy forces

Simulation and Experiments

- Scenario Description
  - The base of the blue force is located on the southern part of the urbane area. The blue force has 8 small weapon UAVs and 8 small sensor UAVs. The physical properties are defined in Table 1 and Table 2.

UAV Type	Speed (Kts)	Endurance (Hrs)	MTBS (Hrs)	MTBF (Hrs)	MTTR (Hrs)
Small Sensor	400	6	2	200	8
Small Weapon	400	6	2	200	8

Table 1. MTBS = Mean time between sorties, TBF = Mean time between failure, TTR = Mean time to repair

UAV Type	GPS Bombs	Seeker Missiles	Submunitions	ESM sensor	GMTI Sensor
Small Weapon	4	8	4	Y	N
Small Sensor	0	0	0	Y	Y

Table 2. Weapon and Sensing Capacity

Simulation and Experiments

- Scenario Description
  - In addition to the small UAVs, the wide body ISR platform collects the raw data of the battlefield information within the range of 100km along the predefined path
  - Moreover the Defensive Support Program (DSP) platform provides sensor data around the blue base .
  - The blue ground force consists of 9 soldiers equipped with small arms. Their goal is to capture and secure two bridges over the river with the close air support provided by 12 small UAVs.

Simulation and Experiments

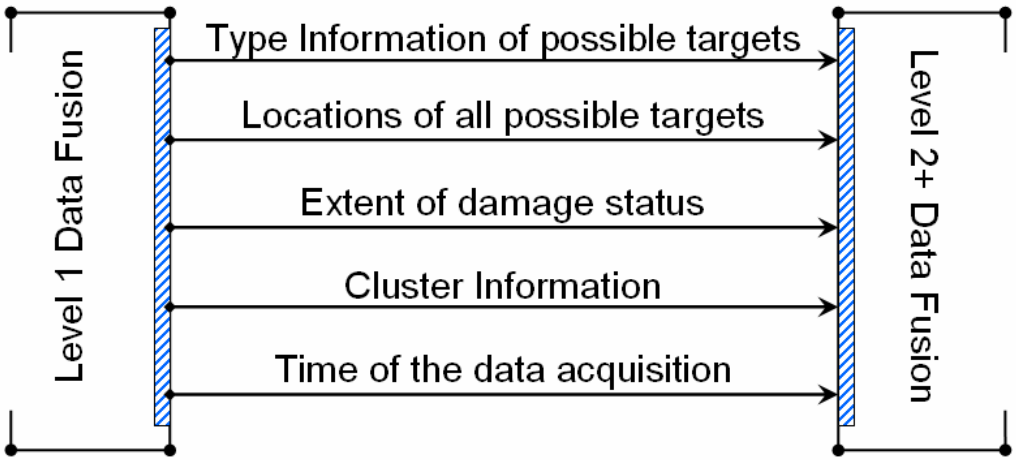
- Scenario Description
  - The red force includes 3 teams of three fighters each with small arms and RPGs (Rocket Propelled Grenade)
  - They also have the Integrated Air Defense spanning the controlled urban areas
  - They are usually deployed near the civilian buildings such as schools, churches, embassies and hospitals (these white buildings are highlighted by in our scenario)
  - In addition, the red force has 16 tanks , which can move quickly along the well paved roads.
  - The objective of the red force is to guard the bridges.

Simulation and Experiments

- Scenario Description
  - We assume the total offence force and total defense force are almost at the same level. There is no dominated one.
  - Then there are several choices for the red force to guard these objectives efficiently. They can deploy all red units to protect one location.
  - However, the blue force can capture other places first.
  - The blue force faces the same dilemma. While blue force plans to concentrate all the units to capture the left bridge, red force can guard it easily by putting all force on it.
  - So the main challenging 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.

Simulation and Experiments

- Data interface between level 1 and level 2+



  - To improve the communication efficiency that is critical in our decentralized markov game level 2+ data fusion algorithm, we use a protocol based data structure, which can reduce the communication load.

```
struct TargetInfo
{
    unsigned long   iTargetType;        //Target Class Information
    unsigned long   iTargetPos;         //Location of the Target
    unsigned int    iTargetDmgStatus;   //Extent of damage status
    unsigned short  iTargetGroup;       //ID of the cluster to which the target belongs
    unsigned short  iTimeStamp;         //Time of the acquisition
};
```

Simulation and Experiments

- A simulation run (Markov Game with Correlated Equilibrium)

Stage 1: Blue side is trying to deploy two teams to the bridge guarded only by one red team via manipulating blue team 2

Simulation and Experiments

- A simulation run (Markov Game with Correlated Equilibrium)

Stage 2: At left bridge, blue side obtained the advantage of attacking one red team with two blue teams.

Simulation and Experiments

- A simulation run (Markov Game with Correlated Equilibrium)

After Battle begins, civilians are supposed to leave the spot

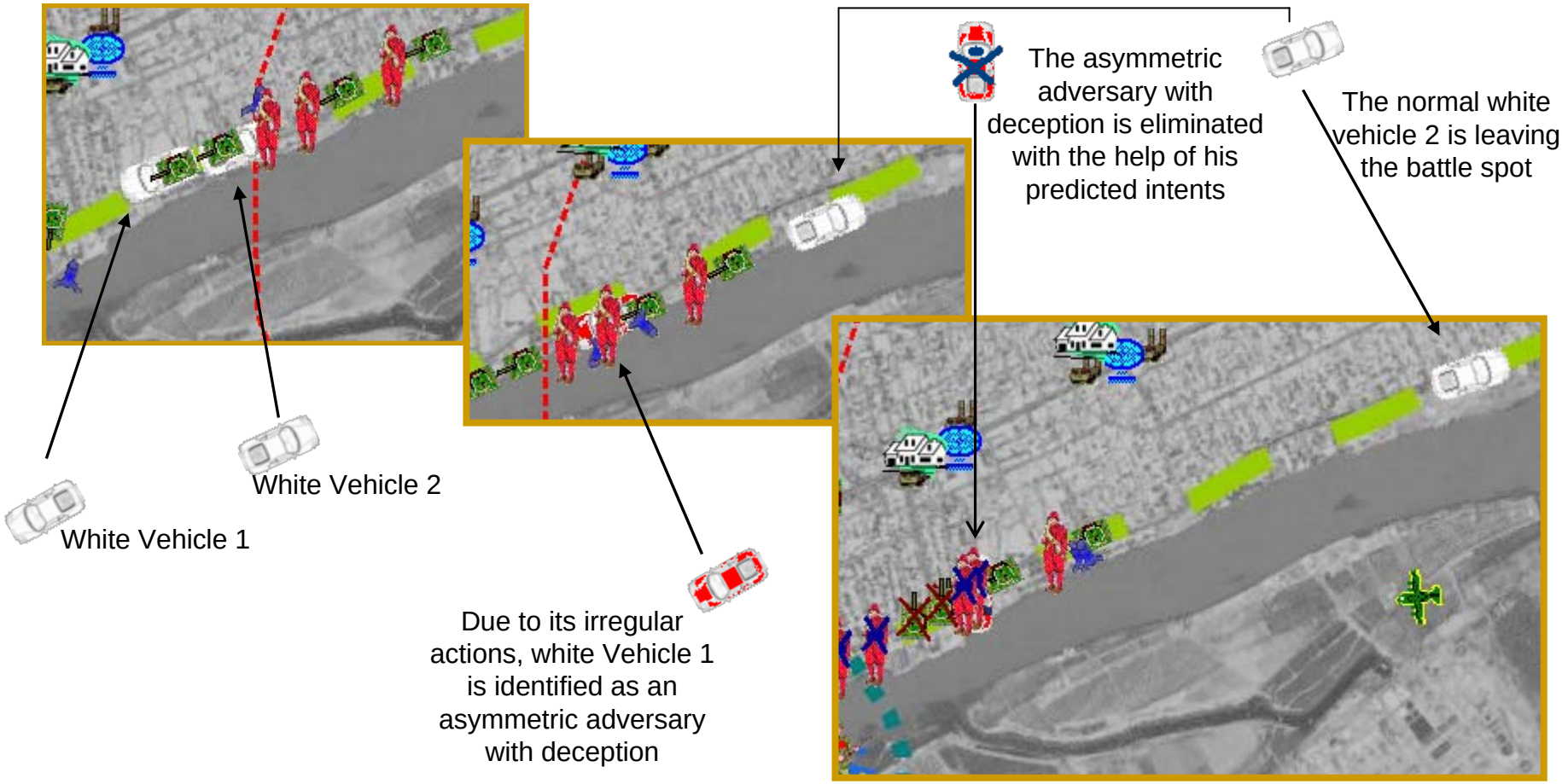
An asymmetric adversary with deception is detected based on his irregular activity

An asymmetric adversary with deception is killed

Stage 3: An asymmetric threat with deception is detected and killed

Simulation and Experiments

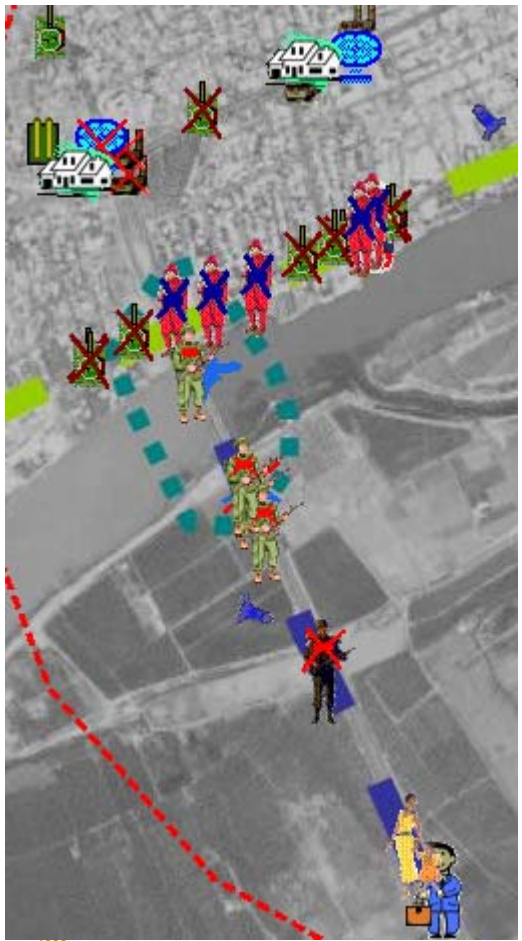
- A simulation run (Markov Game with Correlated Equilibrium)

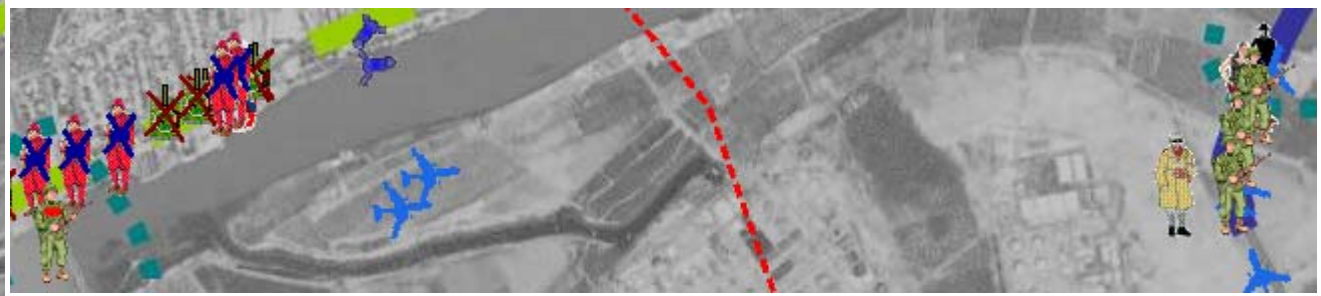


Stage 4: A white vehicle is identified as an asymmetric threat with deception.

Simulation and Experiments

- A simulation run (Markov Game with Correlated Equilibrium)





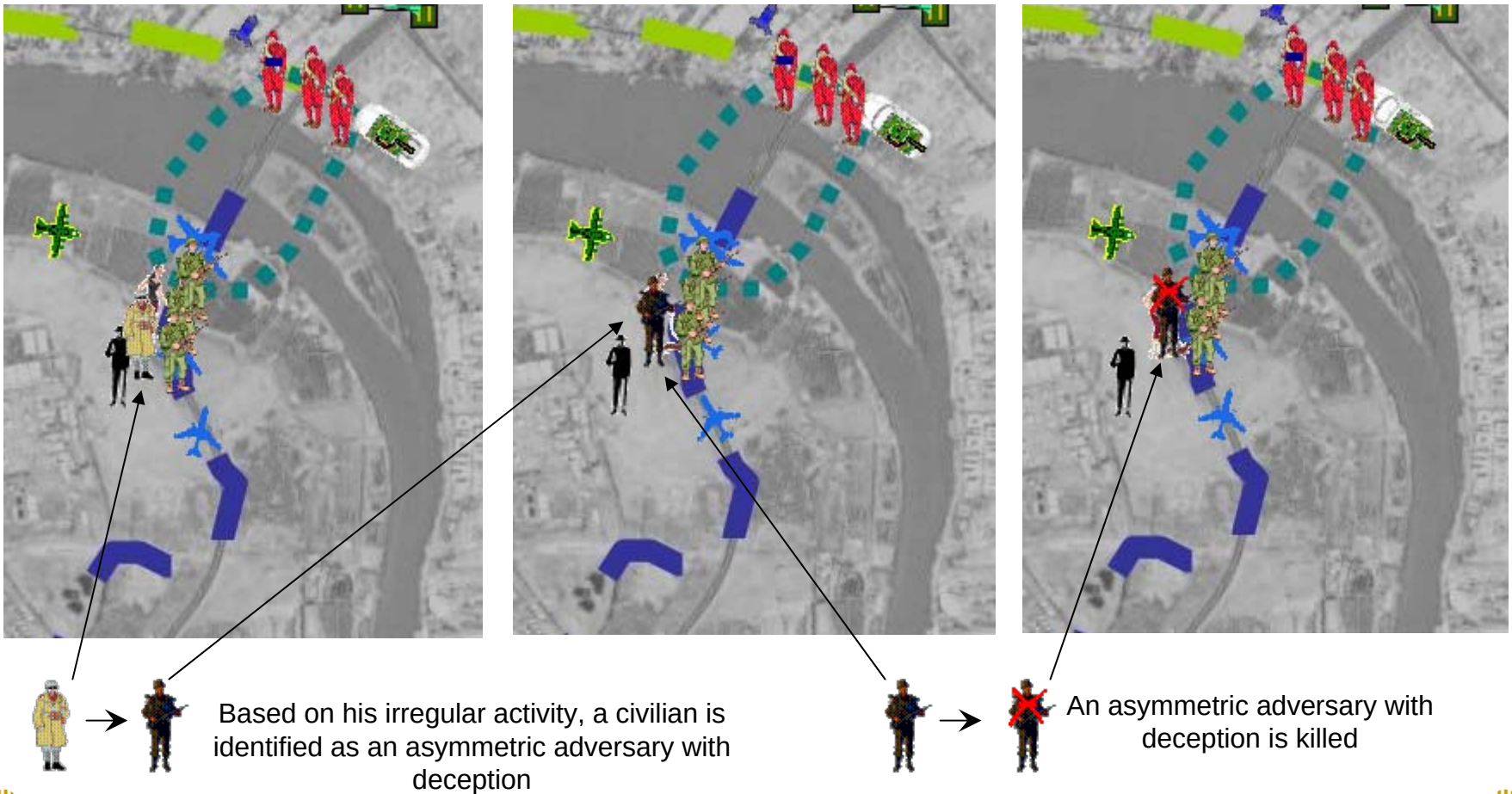
The remaining blue force is divided into two parts: the solider to guard the bridge and the weapon UAVs to help team 3 to capture Bridge 2

By eliminating two red teams and two asymmetric adversaries with deception, blue side captured Bridge 1 with the cost of 5 soldiers and 4 weapons UAVs

Stage 5: Bridge 1 is captured

Simulation and Experiments

- A simulation run (Markov Game with Correlated Equilibrium)



Stage 6: After battle begins at Bridge 2, an asymmetric threat with deception is detected and killed

Simulation and Experiments

- A simulation run (Markov Game with Correlated Equilibrium)

Since there are many red units around the white building, it is destroyed as a collateral damage

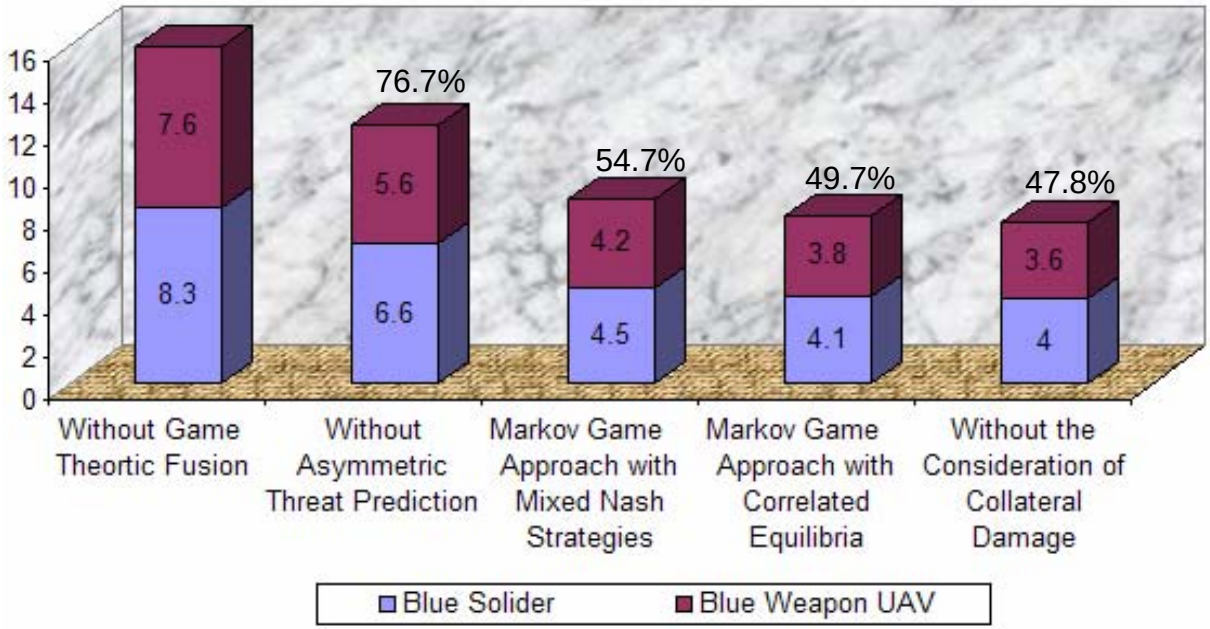
By eliminating Red team 3 and one asymmetric adversary with deception, blue side captured Bridge 2 with the cost of 2 weapons UAVs

The normal white vehicle 2 and civilians are leaving the battle spot

Stage 7: Bridge 2 is captured

Simulation and Experiments

- Simulation Result Summary. (Results are based on 10 runs for each case)



Conclusions

- We proposed and implemented a game theoretic approach for threat intent inference.
- We provided a decentralized Markov Game framework to do threat predication.
- A typical urban scenario was simulated on developed software with connectivity to MICA OEP simulation engine