Modeling Multiple Communities of Interest for Interactive Simulation and Gaming: The Dynamic Adversarial Gaming Algorithm Project

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ABSTRACT

Nowadays, there is an increasing demand for the military to conduct operations that are beyond traditional warfare. In these operations, analyzing and understanding those who are involved in the situation, how they are going to behave, and why they behave in certain ways is critical for success. The challenge lies in that behavior does not simply follow universal/fixed doctrines; it is significantly influenced by soft factors (i.e. cultural factors, societal norms, etc.). In addition, there is rarely just one isolated enemy; the behaviors and responses of all groups in the region, and the dynamics of the interaction among them composes an important part of the whole picture. The Dynamic Adversarial Gaming Algorithm (DAGA) project aims to provide a wargaming environment for automation of simulating dynamics of geopolitical crisis and eventually be applied to military simulation and training domain, and/or commercial gaming arena. The focus of DAGA is on modeling communities of interest (COIs), where various individuals, groups, and organizations as well as their interactions are captured. The framework should provide a context for COIs to interact with each other and influence others' behaviors. These behaviors must incorporate soft factors by modeling cultural knowledge. We do so by representing cultural variables and their influence on behavior using probabilistic networks. In this paper, we describe our COI modeling, the development of cultural networks, the interaction architecture, and a prototype of DAGA.

Keywords: Dynamic Adversarial Gaming Algorithm, Adversary Modeling, Adversary Intent, Community of Interest, Soft Factors, Simulation

1. INTRODUCTION

"Know your enemy and know yourself, you need not fear the result of a hundred battles." (Sun Tzu, The Art of War) Through history, people have been trying to understand their adversaries, in order to better anticipate and counter their actions. Adversary modeling is the natural approach to achieving such a capability that enables us to think "in the opponent's shoes" [14]. One of the biggest challenges in modeling an adversary lies in taking into account the soft factors (or human factors), such as religious, social, political, psychological and economic factors, which influence people's decision making and behavior. In addition, the adversary needing to be modeled is rarely just an isolated entity. In fact, in today's increasing demands to conduct operations beyond traditional warfare, non-combat components (e.g. civilian groups) are also frequently involved [3] and must be accounted for. Thus, it is critical to understand the whole situation, beyond simply modeling the adversary as an isolated individual or homogenous group.

It is obvious that, when solving problems, each entity (either a specific individual or a group) acts based on its viewpoint and context. Furthermore, attitudes, values and perceptions of an entity are not based simply on the here and now, but also one's previous histories, experiences, context, and, in essence, the cultural environment/group they originated from or are currently immersed. As pointed out by Triandis [18], "culture imposes a set of lenses for (people) seeing the world." An entity's perspective of environment and the meaning of other entity's actions will be very different from those that are from a totally different cultural background. In responding to this challenge, we take the approach of modeling each individual or group as an agent and incorporate cultural knowledge into the agent model in the form of cultural fragments, where cultural fragments are small probabilistic networks that can be instantiated and composed to define the specific culture necessary within the domain. As a result, each agent's behavior is under the influence of the cultural information encoded in its behavior model. We can then address the first challenge using a collaborative multi-agent approach where we organize various individuals and groups into different communities of interest (COIs) based on their perspectives of the world. We define a COI as a group of people who share common interests or passions, have some common goals, and a collective concern with their resolution [1, 6, 7]. By enabling interactions among agents within the framework, we can depict the influences and analyze the dynamics among various COIs, and thus predict their possible behaviors in response to a problem or event.

The Dynamic Adversarial Gaming Algorithm (DAGA) project is a multi-agent based gaming environment that can simulate dynamic interactive situation for a particular region of the world. It provides a simulation workspace for encoding knowledge, generating hypotheses, and reasoning, to draw conclusions. This paper describes the architecture of the DAGA framework, our approach to incorporating cultural fragments into agent models, and the implementation of the prototype and demonstration.

2. RELATED WORK

The benefit of applying multi-agent based simulation in wargaming comes from its capability for modeling low level details, which release the burden of handling large amount of scenario inputs and complex dependency relationships from the analysts. In such a simulation environment, complex systems are represented as collections of autonomous agents that behave according to embed governing rules. Aggregated and emergent behavior may rise from the interactions at lower levels. The System Effectiveness Analysis Simulation (SEAS) tool is a representative of such systems [19]. SEAS is designed to model multi-missions and perform campaign level analysis. Agents can represent entities (e.g. military units) at any level within the hierarchies of military structure on the battle field. The interactions between agents and the environment, as well as the interactions among agents themselves are conducted through devices, include weapons, sensors and communication device. Interactions among agents are resolved in time increments, at one minute spreads. Decision making of an agent is based on pre-programmed logic that has been encoded in a component called “user programmed behaviors”; and agent behavior can be changed by modifying the code in a war file. [19]

The Synthetic Environment for Analysis and Simulation (also abbreviated as SEAS) is another multi-agent based simulation system [5]. It has been used to simulate the Department of Defense’s wargaming paradigm in business and economics settings. In the simulation, situation-specific economies based upon mathematical rule-sets are created, which provide functioning goods, labor, asset, bond, and currency markets. The roles and groups have been modeled were the government regulators, firms, households and perpetrators. Households were endowed with demand functions, firms with production functions, perpetrators with political and economic objectives, and government regulators with laws. Typical attacks on an economic system include denial of service, disruption of service, and theft. It has been noted that perpetrators have varied capabilities, intentions and motivations to carry out threats.

As we can see, the agents in these two systems behave mainly based on the capabilities and doctrines that are encoded into them as rules. More recently, it has been realized that understanding the motivations that are influenced by value systems, personality, cultural factors, emotions, and social relationships behind certain behaviors is very important. Thus, a cognitive framework should be introduced into the modeling system to cover the soft factors from the human side of the equation. Socio-cultural gaming and simulation is a result of such an effort [15, 16]. It focuses on modeling behaviors of leaders and followers and identifying the components needed for a role playing game. One assumption is that the majority of conflicts are centered around resource control. In the model, resources available to a group and its members include political goods (jobs, money, food, training, healthcare, etc.), rules within the group and security measures to impose on other groups, and popularity and support for the leadership as voted by its members. Each agent includes an intelligent component, called a performance moderator function server for simulating human behavior such as perception, stress and coping style, personality and culture, social relationships, and emotional reaction and affective reasoning about world. In the simulation, the environmental situations are categorized, and each category implies that certain strategies should be applied by an agent. Under each strategy category, there are sub-tasks and missions that can be carried out. For example, under “Grand Strategy Category” “Economic War on C”, there are missions like “Block Goods” and “Deny Infrastructure”. The cultural values and personality traits are represented through Goals, Standard and Preferences trees. Each tree nodes are weighted with Bayesian importance weights. Each agent acts in attempt to maximize its utility within the iteration of games.

In the DAGA project, we take this one step further to incorporate soft factor impacts explicitly into our knowledge representation structure for abductive reasoning. It should provide a systematic way of representing causal relationships between the cultural, political, economic elements and the goals/interests of an intelligent entity, and enables a multi-agent based system to produce simulation environment that is more realistic.

3. SYSTEM DESIGN

DAGA is a multi-agent simulation environment for COIs of adversaries, allies, and neutrals to interact with each other. Within this context, one entity's decision making and behavior are influenced by other's opinions and actions. The framework is designed to meet the following goals:

- Expand adversarial gaming algorithm to support an agent-based dynamic environment, by modeling COIs as various intelligence agents that act based on the reasoning outputs from embedded probabilistic behavior models, capturing interactions among these agents, and evaluating their responses.
- Support agent (represents a COI) plug in, where new agents should be easily added into the simulation environment and join the interactions as there is a require from the scenario, with minimum extra system configuration work.
- Develop algorithmic techniques to incorporate soft factors into agents' behavior models, which is the key for the system to be able to predict COI's responses to social, cultural, political and economic actions. It shall enable predicting based not only on current situation and adversary capabilities, but also on adversary's cultural dimensions and other soft factors.
- Enable the model system to dynamically evolve with the environment changes, and eventually achieve the capability of providing adaptive strategy selection in multi-culture adversarial games in an agent-based dynamic adversarial environment.
- Provide distributed access to hierarchic COIs within context of an agent framework. The goal is to extend the capability to a multiple machines/nodes simulation platform that is able to handle as the computational complexity as the number of considered components in the models grows.

The DAGA framework is comprised of two parts: an agent model and an agent interaction model. The agent model embedded in each COI agent is responsible for its decision making and generating possible actions/reactions of the agent. The interaction model provides an environment where all the interactions among COI agents happen. In brief, in response to the external inputs and other agents' actions, a registered agent reasons based on its perception of the world, and posts its actions to the interaction environment. The posted actions, their outcomes generated by the constraints, rules, and domain knowledge inside the interaction model, and new external inputs (exogenous events) are observed by all the agents and taken as new evidence inputs for each agent model; thus, starting the next cycle of reasoning and action.

3.1 Agent model

For a COI agent to behave realistically, the agent model must capture the intent of the COI. In our view, the intent covers the goals that COI is pursuing (e.g. the desired end status), the reasons for it to set such goals, and the actions that the COI might take in order to achieve them. In order to capture the intent of a COI, we construct the corresponding agent model with three major components: foci/goals, rationale network, and action network [2, 10, 11, 14, 17]. Within the agent model, foci/goals is a prioritized goal list that represents goals or objectives. It captures what the COI agent is doing, which evolves over time. Rationale and Action network are both probabilistic networks. Rationale represents the influences of beliefs, both about the agent itself and its perception on others, on agent's goals and high level actions associated with those goals. Action network represents the detailed relationships between goals and possible actions to carry them out. It captures how the agent might do it. Due to the inherent uncertainty involved in behavior modeling, we use Bayesian Knowledge Bases (BKBs) [12, 13] as the knowledge representation for the rationale and action network. BKBs are a generalization of Bayesian Networks [9] and designed keeping in mind typical domain incompleteness to retain semantic consistency and soundness of inference. One additional benefit from using BKBs is reducing the complexity of developing probability tables typically associated with Bayesian Networks.

When constructing the probabilistic networks (i.e. BKBs), important elements are identified and represented by random variables in the network. In our agent model, these random variables are classified into four classes:

- Axioms: represent the underlying beliefs of COI agent about self – e.g., religious conviction, idolization of leaders and martyrs, respect, materialism, role in society, psychological states like hopelessness, COI demographics, capabilities, personal involvement, value, honor, etc.
- Beliefs: represent the beliefs regarding other COIs – e.g., enemy of God, decadence, capabilities, moral, etc. Like the Axioms, the Beliefs are not necessarily to be reasonable ones.
- Goals: represent the desired end-states – e.g., support insurgency, fight unbelievers, defeat enemy, survive, make profit, please leaders, etc.
- Actions: represent the actions to be used to realize goals – e.g., contact others, buy instruments for nuclear project, transfer bio-material, suicide bombing, etc.

The four types of random variables are arranged into two networks. In short, Goals are supported by Beliefs and Axioms, and Actions are used to carry out certain Goals. The Goals are further categorized into concrete goals and abstract ones, where the concrete goals are those that can be carried out directly by certain actions, and the abstract goals are general ones that can be decomposed into more concrete sub-goals. The rationale network contains all four kinds of variables. It is used for inferring the adversary's short-term and long-term goals. Once the goals are determined, the action network is used to reason out what the most likely agent actions will be. The action network contains the entire set of Action variables and any concrete Goal variables. Hence, a probability distribution is defined over the relationships among these variables in the networks in each agent model; and as a result, the agent behavior is determined by reasoning process over the networks, in which various observations are taken as evidences.

As we discussed previously, in the reality, intentions of COIs are greatly influenced by existing religious, political, economic, social, and cultural factors. Thus, it is critical to be able to capture these soft factors in the agent model. Since we use BKB networks to predict potential COI actions, it is natural for us to capture the soft factors influence, such as cultural influence, from various aspects that include religious belief, trust and honor, social hierarchy, and perceptions of others, in the BKB networks. We extract the key cultural variables, their relationships and influence they have on COIs' behaviors by studying a variety of social science theories, socio-economic-political data, and then construct pieces of small probabilistic networks that are called cultural fragments. The important elements of soft factors can be directly captured in the Belief and Axiom variables in the rational network, e.g., the network can have an axiom variable "Believe in radical (Islamic) religious doctrines" (See examples in the network shown in Figure 3 below, which is an example of rationale networks for one COI agent). Therefore, we enable an abductive reasoning process in the agent model to develop hypotheses, as well as constitute the interpretation of the evidences that take into account the soft factors. Figure 1 shows a high level view of the components in the agent model.

When constructing BKB networks, we create small network fragments. Each network fragment covers a piece of information/knowledge from a specific viewpoint. The small size of these networks has the benefits of easy maintenance where the existing cultural fragments are modifiable in order to represent further refined cultural data. Eventually, the accumulated cultural fragments become a rich knowledge base, and retrieving and composing relevant fragments from the knowledge base can give rise to a working network that depicts the bigger picture concerning some specified scenario for a COI agent.

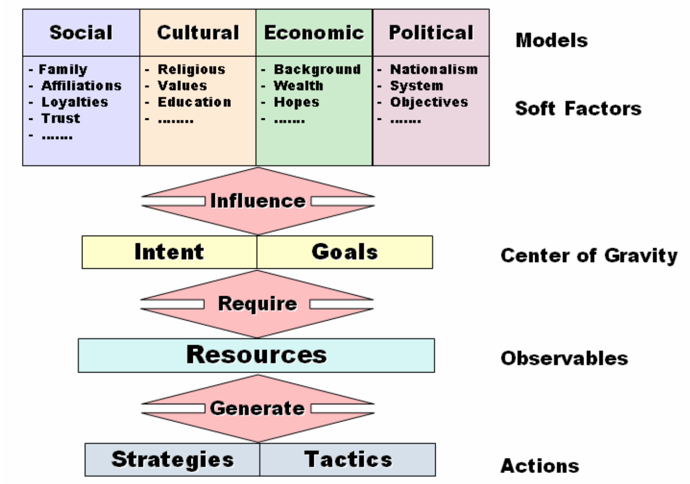

Figure 1. High level view of agent model components

3.2 Interaction model

Each “hot” region is composed of multiple COIs that vary in their interests, political attitudes, cultural backgrounds, economic status, etc. There are definitely groups that have conflicting goals. On the other hand, there may also be groups that have the foundations to build collaborative relationships, which can either be loose or fairly tight. More fundamentally, a COI’s opinions and responses to an event are influenced by other parties involved in the situation; and the interests and goals of a COI might be shifted or even changed by these influences, which means that the relationships among COIs might also change. All these contribute to the dynamics of the environment.

The most basic relationship between two agents, in the agent framework, is that the decisions and/or actions of one agent would be observed by the other one, which would then influence its view of the world. A hierarchical relationship between two COIs is more complex. For example, an individual is a member of a terrorist cell, and this cell in turn belongs to a particular terrorist group. In this case, each agent has a specialty role, and acts within a larger group decision-making context that is more confined. The behaviors of agents that are at lower level of the hierarchy can then (1) influence the other agents directly, and/or (2) show aggregated impacts on the agents that in the higher level of the hierarchy; the influence upside down the hierarchy should be stronger, for example, there might be an order passed from the commander.

The interaction model represents governing rules of mapping influence among COIs, and provides an environment for agent interactions to happen. It contains domain knowledge, which is an OWL-based Web ontology called the common operation ontology (see Figure 2), for mapping impacts of various event inputs and actions of other COIs into a particular agent model. The common operation ontology encodes semantic relationships among soft factors, situational states, and COI responses, which enable DAGA to classify, infer, and translate game actions and state into appropriate COI modeling constructs. With assistance from the common operation ontology, the interaction model passes the external inputs from the user to registered agents (and agent models), and updates/maintains the states of the world from step to step. The architecture of the interaction model is shown in Figure 2, where each COI agent has its own model capturing its unique perception of the world. When an event happens (i.e., a problem rises), each agent takes some actions, which are posted to the interaction interface. These actions then become observables to certain other agents. In the next iteration, each agent will take account the observed behaviors of others, as well as new external inputs (from the user) if there is any, in their decision making process. The user can observe how different COI agents acts/reacts in responding to his/her inputs and other agents’ actions. A COI agent can be plugged into the system at anytime; and there is no limit to the number of agents involved in the system.

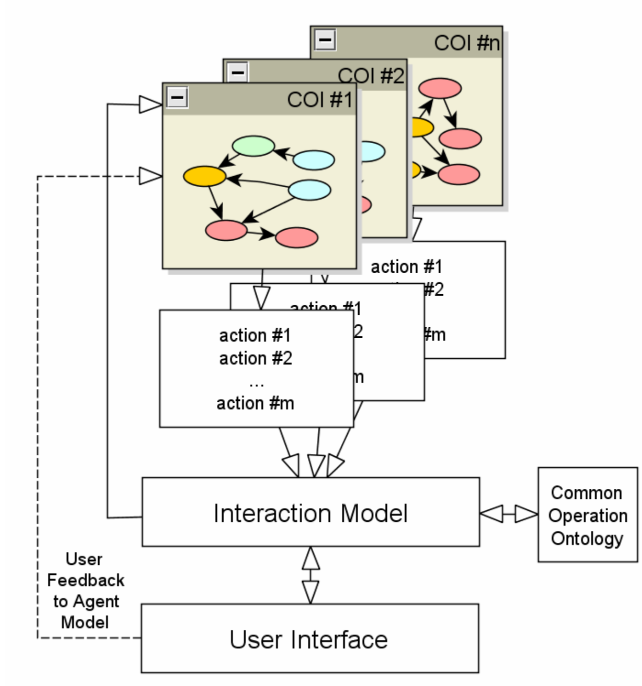

Figure 2. Interaction Model Architecture

4. PROTOTYPE AND DEMONSTRATION

The demonstration is for the purpose of illustrating the importance of capturing the cultural specific elements of the COIs we are modeling, and showing the system dynamics which can be achieved from the interaction among COI agents. The scenario used concerns the situation in a region of unrest (politically, religiously, economically, etc.), where coalition forces led by the US military have the task of peace keeping and reconstruction, however, they might be viewed as occupiers by the local populations. It contained four COIs. There were two different insurgent groups, a religious group and a secular group. The religious insurgent group consisted of people mainly driven by their religious beliefs; for example, they believed that existence of allied forces was part of a Crusade, and their goal was to defeat the unbelievers, etc. On the other hand, a secular insurgent group was composed of people who felt the allied forces invaded their homeland, and/or felt hopeless about their lives for which they blamed the "intruders"; and then their short-term political goals were more dominant. Besides the insurgent groups, there were also two different types of individuals: (1) individuals who tended to join insurgence for religious reasons, and (2) individuals mainly concerned about how to survive. Obviously, the first type of people formed the foundation for the religious insurgent groups, while the people mostly concerned about surviving was the majority of the population.

The presence of coalition forces (or US military) could also be modeled as COI agents and join the interactions with other COIs directly. We chose to treat their behaviors or actions as external input events to the system for simplicity. By doing so, we could also observe more clearly what kinds of behavior and/or what sequence of actions would be triggered by certain actions from the coalition forces. The scenario, although not an actual historical event, was based on the information we extracted from our study on social science data from historical and current cases studies [4, 8].

In the simulation, we created one agent model for each of the four COIs described above. The common operation ontology encoded sets of possible coalition actions, and mappings of actions and cultural dimensions to goals, actions, and beliefs in different agent models. Each selected coalition action presents an evidence (i.e. game state) to COIs, The system charts resultant output actions after each update (presentation of evidence), and monitors trends in selected COI outputs. The outputs being monitored are actions of certain COI agents considered to be important and selected in order to observe trends (see Figure 4). The interaction model is responsible for the selection of outputs for monitoring.

Figure 3 shows a BKB network we created for a religious insurgent group. It followed the semantic structure we described in Section 3.1. In the simulation, the agent which contained this network represented the COI of the religious insurgent group. As we can see, this small network captured a number of cultural factors that influence the agent's actions, such like religious belief, trust and honor, social hierarchy, and perception of others.

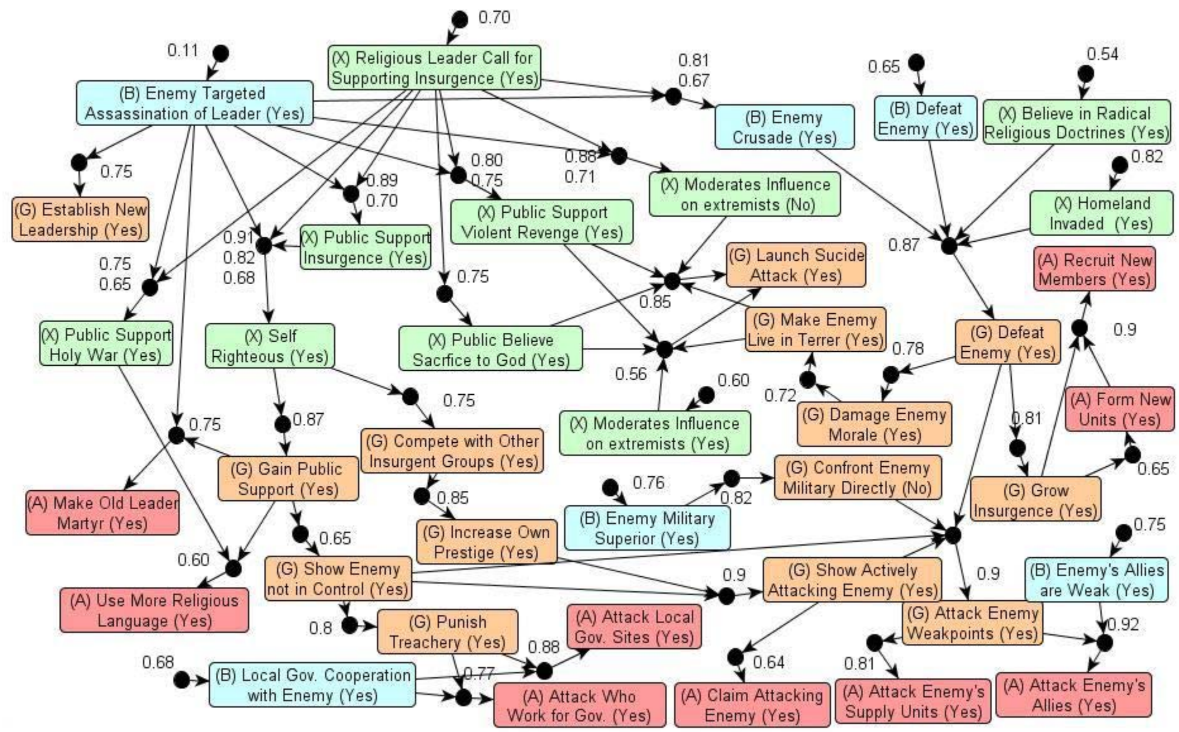

Figure 3. A BKB fragment (partial network) for religious insurgent group used in simulation. In the network, the nodes in rectangles are instantiation nodes; the nodes in dark circles are support nodes. In BKBs, the instantiation nodes are labeled nodes that represent unique specific assignments to individual random variables; the support nodes carry the probabilities for each of the conditional probability rules – each rule is of the form: antecedents (the instantiation nodes incoming to the support node) implies consequent (the instantiation node pointed to by the support node). The influence between nodes propagates via the conditional probability along the arcs. (X) stands for Axiom, (B) stands for Belief, (G) stands for Goal, and (A) stands for Action (see Section 3.1).

When an event happened, it would trigger COI agents to act in one of two ways. First, if an event was already covered by the probabilistic networks in the agent model, then it could be simply set as direct evidence. For example, the nodes "(B) Enemy targeted assassination of leader (Yes)" and "(X) Religious leader call for supporting insurgence (Yes)" in the network shown in Figure 3 could be set as evidence. Second, the influence of an event could be mapped onto certain nodes in the network through the knowledge component interaction model. For example, if coalition forces' actions were perceived as "intentionally offending the local religious beliefs," then either the probability value for "(B) Enemy crusade (Yes)" would increase, or be set as evidence, which is decided by the interaction model currently coded in an XML file. Another example would be if coalition forces announced that the goal of a military action was to establish a stable state structure, and set up a withdrawal time table, the probability setting for "(X) Homeland invaded (Yes)" would be decreased.

The influence of the actions from various COI agents would propagate through the same channels; for example, people joining insurgency and street protests against coalition forces would be translated as evidences “(X) Public support insurgence”, “(X) Public support holy war”, etc. in the network shown in Figure 3.

In the simulation experiments, we defined three sets of events (the actions from the coalition forces), and then running the experiments by triggering these actions in different orders as shown in Table 1. Intuitively, various COI agents would react to the events in their own ways. When the events happened in different order, their reactions would also be affected. As we observed in the simulation output, religious individuals’ behavior would not change significantly in response to events such as “Coalition distribute supplies” and “Coalition raid”, because their points of views were fairly focused towards religious goals. Their actions were, however, were more influenced by the religious leaders. On the contrary, the behaviors of the population majority were different. The living conditions and personal experiences would have significant impact on their actions and reactions. Similar results were also observed for the religious insurgency group versus the secular insurgency group.

Table 1. Three sets of events (actions from coalition forces) used for simulation. The events coved in each set were generally the same, however, they were designed to happen (input into the simulation environment) in different orders.

	Events in time order
Sequence 1	Coalition Distribute Supplies Coalition Meet Religious Leaders, and Religious Leader Call for Peace Coalition Raid Coalition Assassinate Insurgent Leaders
Sequence 2	Coalition Raid Coalition Assassinate Insurgent Leaders Coalition Distribute Supplies Coalition Meet Religious Leaders, and Religious Leaders Call for Peace
Sequence 3	Coalition Raid Coalition Assassinate Insurgent Leaders Religious Leader Condemns Heathenry Coalition Distribute Supplies Coalition Meet Religious Leaders, and Religious Leaders Call for Peace Clear Evidence (Religious Leader Condemns Heathenry)

An example of simulation outputs is shown in Figure 4 showing the responses of the religious group to simulation inputs: event sequence 1 and sequence 3 (Table 1). Event sequence 1 corresponded to the intention of coalition forces to build “goodwill and trust” in the region before taking any actions. In the panel labeled “Monitored Action,” we can see that the action “Call_for_Holy_War” peaked at just under 0.5. For event sequence 3 which represented the coalition forces executing their actions first, then trying to do damage control, the action of “Call_for_Holy_War” peaked at 0.75. Only after the coalition took the action to meet with religious leaders and the religious leaders subsequently called for peace, its probability value dropped to 0.5.

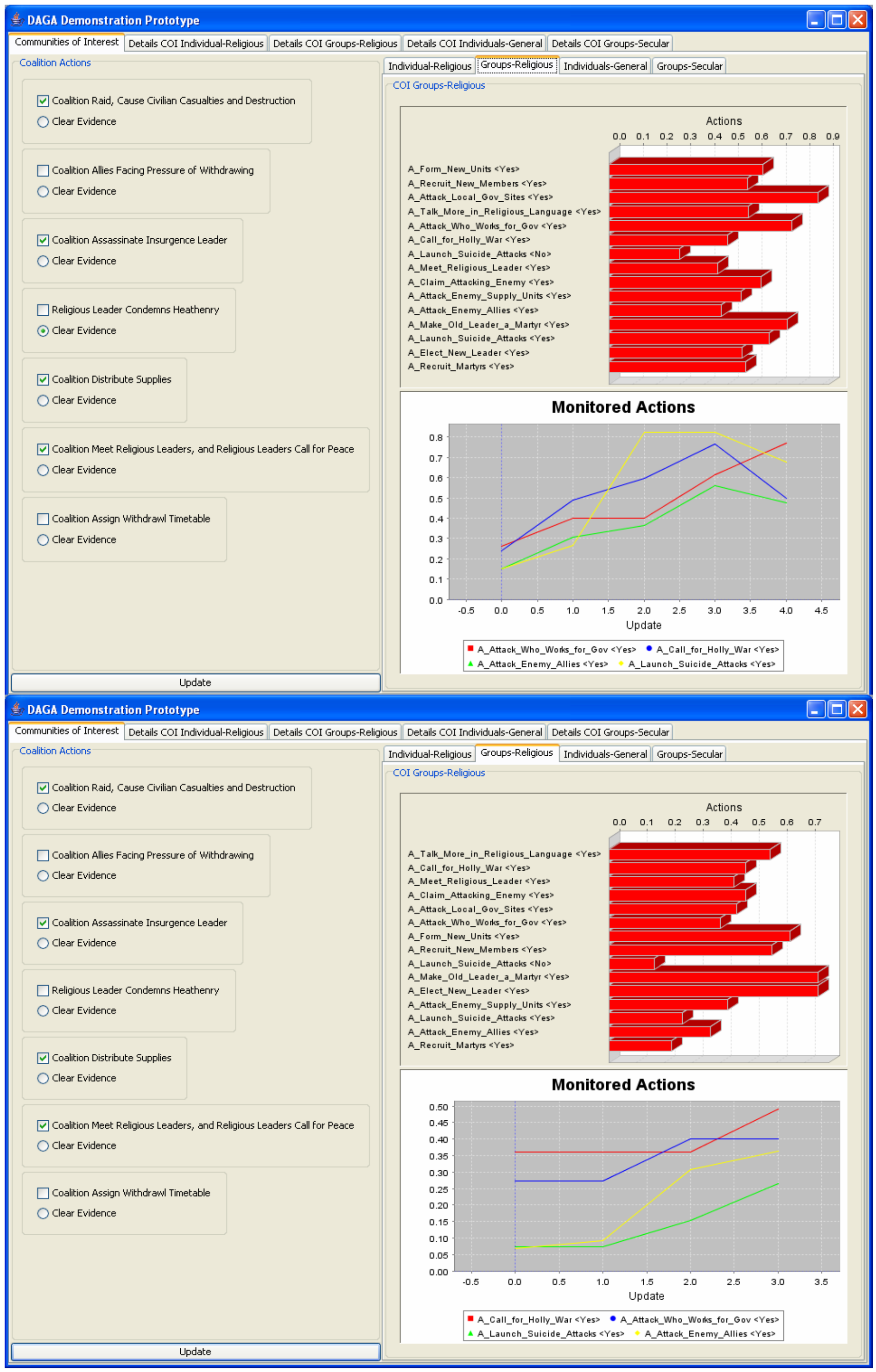

Figure 4. Simulation behavior outputs of religious insurgency group in response to event input sequence 1 (top) and event input sequence 3 (bottom). In the interface, the left side displays the events that can be used as inputs. On the right side, the upper panel shows the actions with weights (probability values) and the lower panel shows the COI actions being monitored.

5. SUMMARY AND DISCUSSION

The increase in demand to perform tasks beyond traditional warfare, such as limited conflict warfare, asymmetric warfare and peace keeping missions, has created new challenges in mission planning. For the same reason, there are also increasing needs for improved simulations to assist in situational awareness in this new environment. A realistic adversarial simulation beyond simply modeling attrition principles requires a system capability for predicting with continual assessment of the intentions and courses of actions of all parties that are involved in the situation. This includes adversarial forces, allied forces, as well as the local civilians and religious and political groups. Unfortunately, current approaches are limited to “human assessment capabilities.” In the DAGA project, we were able to incorporate soft factors, such as cultural dimensions, into adversary behavior to predict attitude formation and behavioral changes. The important elements — soft factors were extracted from sociological theory and literature, and inserted into BKB networks. Since the BKB networks embedded in each agent form the basis for predicting the intentions and potential agent actions, the agent can react to social, cultural, political and economic factors.

Most typical approaches to adversarial gaming also view the adversary as a single isolated entity, which works well from the strategic policy point of view. However, they can only provide limited insight into how a group reacts to specific events. A main reason is that considering only a homogenous adversarial entity can model neither the dynamics among the components that comprising the entity nor other parties’ influences. We used COI agents, in DAGA, to represent people with similar interests and goals. This approach enables us to logically group people together. Encapsulation of the models/algorithms to produce their respective results in the COIs can significantly improve system efficiency. On the other hand, DAGA is capable of modeling a specific individual (e.g. a key leader in an insurgent group) and the hierarchical structure of an organization that itself contains multiple COI agents. We believe this approach can provide us flexibility to be able to run simulations that focus on certain COIs and provide enough insight at the necessary level of detail, while at the same time, keep a proper level of aggregation in order to avoid overwhelmingly complex system analysis.

A fundamental challenge in COI research is on how to achieve the sharing of understanding among collaborative COIs. In a multi-agent framework, the challenge becomes how to pass the influence from one COI to another, where the influence is based on the one agent’s understanding of others but not necessarily a completely correct understanding. In DAGA, interactions among COI agents were guided through semantic mappings encoded in an OWL-based Web Ontology component, called the common operation ontology. With the common operation ontology, the interaction model translates and passes the external inputs, actions from registered COI agents, and possible outcomes of those actions and events into agent models. The agent models take the inputs from the interaction model as evidences, and behave according to abductive reasoning results. Notice that the interaction model provides an environment where various influences can be passed into COI agents while at the same time, the output from each agent also influences and changes the environment.

The simulation experiment demonstrated that the DAGA framework can serve as a dynamic gaming environment that enables modeling and simulating the adversarial (and other parties’) interactive behaviors on a community-to-community basis. These experiments depicted how coalition actions affect adversary goals and beliefs and predicted the responses of COIs. We demonstrated that soft factors can be included in adversarial gaming algorithm by encoding them into BKB networks that are used by the agent model in its inferencing process. It provides a “validated” model of how culture influences behavior. The dynamic simulation environment allows analysts to gain insight into the problem space, validates the information used to drive the decision process, and perform “what-if” analysis. The causal relationships about physical/logic/cultural reasons for a COI’s behavior and the influences among COIs captured in the models can provide explanations on why a COI behaves in certain ways. It also allows the analysts introduce various “evidences” into the gaming environment, to test how to influence the mind and behavior of targeted COI. Finally, DAGA provides an experimental environment for testing Blue’s understanding of the adversaries. If a specific COI agent acts significantly different than what has been anticipated, then it suggests (or warns) that the corresponding model does not correctly reflect the reality and needs to be updated, or there must be certain critical information or knowledge that has not been accounted for in the model, which in most cases pinpoints the need for missing information (i.e. identifies weakness in hypothesis).

6. WHAT'S NEXT?

We have constructed a multi-agent based simulation framework that is capable of logically grouping people into various COIs based on their interest and goals, and incorporate soft factors influence into agent modeling. One obvious future goal the left for us is to extend the DAGA system, from a single machine prototype to a distributed platform with multiple machines/nodes.

Another important feature of a dynamic system is adaptation. A system must be able to learn and evolve along with the changing environment. We envision dynamic learning and evolution in DAGA to happen in both the agent model and the interaction model. As described previously, properly incorporating cultural knowledge into the modeling process is necessary for correctly modeling the adversarial behaviors. In our approach, we use cultural fragments, which can be instantiated and composed to define any specific culture necessary within the domain, to depict cultural knowledge, identifying the relevant fragments, modifying according to the current inputs, and merging them properly to form the working network is the key to achieving system adaptivity.

We will continue our work on developing a rich cultural network fragment library, and developing fusion algorithms based on a pooling procedure of multiple samples from network fragments. It is also necessary to build a systematic approach that generalizes the knowledge fragments (the BKB network fragments created based on various behavior models and extracted from case studies) for easy reuse/creation of models that incorporate soft factors. For example, is it possible to generalize beliefs/axioms from a terrorist group and apply it to an inner city gang where similar soft factors will impact the intention of the involved parties (e.g. economic despair, belief in no opportunity, etc.)?

At the interaction model level, our objective is to enhance integration capabilities of the common operating ontology**.** This component determines how information from existing gaming/military environments may be programmatically accessed to populate and drives calculations that directly effect soft factors and actions. The future interaction model should have the capability to support the semantic relationships necessary for composing BKB fragments for DAGA to learn from its simulation experience (episodic learning). As the game progresses, predicted outcomes and their explanation, along with the differences between predicted and observed actions, are captured by the system. The feedback will enable the COI agents to evolve over time, which include new individual and group experience into COI, represent the changing composition of agent models, focus and prune search space, bound optimization, guide scheduling, and better allocate resources.

For DAGA to be effectively utilized in "what-if" analysis, some additional functionality will be added into the system, which includes history recording and explanation tracking. History recording enable the system to step back to its previous status, and then allows the analysts to re-input a different set of observations and study how COIs would react. Explanation tracking will provide the ability to trace the logic of certain behavior all the way up to the high level beliefs, which can facilitate insights for analyst on why certain things are happening and how to influence the COIs' thoughts and behaviors.

7. ACKNOWLEDGEMENTS

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REFERENCES

1. William Aiello, Charles Kalmanek, Patrick McDaniel, Subhabrata Sen, Oliver Spatscheck, and Jacobus Van der Merw (2005). "Analysis of Communities of Interest in Data Networks". In Proceedings of Passive and Active Measurement Workshop, Mar. 2005.
2. Benjamin Bell and Eugene Santos, Jr. (2002) "Making Adversary Decision Modeling Tractable with Intent Inference and Information Fusion", in the Proceedings of the 11th Conference on Computer Generated Forces and Behavioral Representation, Orlando, FL, 2002

3. Curtis L. Blais (2005) *Modeling and Simulation for Military Operations Other Than War (MOOTW)*, MV4920 Course Summary, Naval Postgraduate School MOVES Institute, Monterey, CA, 15 December 2005.
4. Mia Bloom (2005) *Dying to Kill: the Allure of Suicide Terror*. Columbia University Press
5. Alok R. Chaturvedi, Mukul Gupta, Shailendra Raj Mehta and Wei T. Yue (2000) "Agent-Based Simulation Approach to Information Warfare in the SEAS Environment." in *Proceedings of the 33rd Hawaii International Conference on System Science*, 2000.
6. Chief Information Officer, Information Management Directorate, DoD (2004) Communities of Interest in the Net-Centric, DoD Frequently Asked Questions.
7. Gerhard Fischer (2001) "Communities of Interests: Learning through the Interaction of Multiple Knowledge Systems". *The 24th IRIS Conference*, Bergen, Norway, pp. 1-14.
8. Robert Pape (2005) *Dying to Win: the Strategic Logic of Suicide Terrorism*. Random House, Inc
9. Judea Pearl (1988) *Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Inference*, Morgan Kaufman, San Mateo, CA, 1988.
10. Eugene Santos, Jr. (2003) "A Cognitive Architecture for Adversary Intent Inferencing: Knowledge Structure and Computation". in *Proceedings of the SPIE 17th Annual International Symposium on Aerospace/Defense Sensing and Controls: AeroSense 2003*, Orlando, FL, 2003
11. Eugene Santos, Jr. and Allesandro Negri. "Constructing Adversarial Models for Threat Intent Prediction and Inferencing". *in Proceedings of the SPIE Defense & Security Symposium*, Vol. 5423, Orlando, FL 2004.
12. Eugene Santos, Jr. and Eugene Santos, S., (1999) "A Framework for Building Knowledge-Bases Under Uncertainty", *J. Exp. and Theoretical Artif. Intelligence*, 11, 265-286, 1999.
13. Eugene Santos, Jr., Eugene Santos, S., and Solomon Eyal Shimony (2003) "Implicitly Preserving Semantics During Incremental Knowledge-Base Acquisition Under Uncertainty", *Int. J. of Approximate Reasoning*, 33(1), 71-94, 2003.
14. Eugene Santos Jr. and Qunhua Zhao (2006) "Adversarial Models for Opponent Intent Inferencing". In Alexander Kott and William M. McEneaney (eds) *Adversarial Reasoning: Computational Approaches to Reading the Opponent's Mind*. Chapman & Hall/CRC, Boca Raton, London, New York
15. Barry G. Silverman (2005). "Human performance simulation". In J.Ness, D.Ritzer, & V.Tepe (Eds.), *The Science and Simulation of Human Performance* (Chapter 9). New York: Elsevier.
16. Barry G. Silverman, Gnana Bharathy, Michael Johns, Roy J. Eidelson, Tony E. Smith (2006) " Socio-Cultural Games for Training and Analysis" *Technical Report*, available at: http://www.seas.upenn.edu/~barryg/CultureGames.pdf
17. Joshua Surman, Robert Hillman, and Eugene Santos, Jr. (2003) "Adversarial Inferencing for Generating Dynamic Adversary Behavior". in *Proceedings of the SPIE 17th Annual International Symposium on Aerospace/Defense Sensing and Controls: AeroSense 2003*, Orlando, FL. 2003
18. Harry C. Triandis (1994) *Culture and Social Behavior*. McGraw-Hill, Inc. New York, St. Louis, San Francisco, Auckland, Bogota, Caracas, Lisbon, London, Madrid, Mexico City, Milan, Montreal, New Delhi, San Juan, Singapore, Sydney, Tokyo, Toronto
19. Andrew W. Zinn (2004) "The Use of Integrated Architecture to Support Agent Based Simulation: An Initial Investigation" Air Force Instituted of Technology, Graduate School of Engineering and Management, Thesis, March 2004.