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COMMON PROBLEMS AND HELPFUL HINTS TO SOLVE THEM: LESSONS LEARNED IN INTEGRATING COGNITIVE MODELS IN LARGE-SCALE SIMULATION ENVIRONMENTS

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ABSTRACT

The application of M&S simulation technologies to advanced analysis and training functions throughout the DoD has led to an increasing need for higher fidelity representations of human decision-making behavior than is currently available in most military simulation behavior engines. The appropriate path to meet this need is to incorporate cognitive models from the Human Behavior Representation (HBR) community that provide psychologically-rooted representations of decision-making behavior and performance. There are significant challenges associated with the integration of these models within complex simulation environments, however. Here, we attempt to identify some of these challenges and provide design strategies to overcome them. Specifically, we provide strategies for selecting appropriate modeling resolution for specific applications, dynamically managing the resolution of those models throughout a simulation run, and dealing with the general mismatch of sensor and control data between simulation environments and HBR models.

1 INTRODUCTION

Increasingly sophisticated models and simulations are being developed by DoD to support a range of analysis and training functions: analysis applications include the support of research, development and acquisition decisions (e.g., Simulation Based Acquisition), development of general doctrine and tactics, and generation of specific operational plans; training applications include general "training for war", ongoing proficiency maintenance, and more focused mission rehearsal activities. As DoD operational plans and systems have grown in complexity, demands made on the modeling and simulation (M&S) base are growing correspondingly, with increasing requirements for greater levels of simulation fidelity and usability (DMSO 2000).

As the application of M&S tools has moved beyond the modeling of isolated physical systems (e.g., high fidelity aircraft system and subsystem models supporting analysis throughout the design cycle) to large-scale engagement simulations to support analysis and training at the joint force level, it has become increasingly important to effectively represent human elements, since battlespace dynamics are inherently driven by human decision-makers at all levels of operations. As a result, high fidelity representations of that decision-making behavior is required within military simulations to study advanced issues such as tactics development or to effectively train warfighters within a dynamic and reactive environment that provides realistic responses to trainee actions.

Most large-scale M&S environments provide some level of behavior modeling capabilities to manage the dynamics of the battlespace. These embedded behavior engines generally rely on either pre-defined behavior scripts or on simple decision tree logic. Through scripting, the entity's decisions and actions are fully defined during the scenario generation process, thus eliminating any ability to react to the dynamic battlespace. Some of that reactive capability is achieved using decision trees, but again, the scenario generator must be able to classify and represent all possible decision points and options prior to simulation execution, which is most difficult considering the unpredictability of human participants (e.g., trainees) that may interact with the modeled entity. Also, such methods do not effectively model the decision-making *processes* of humans, with all of their individual skill sets and basic performance limitations. As a result, such approaches to modeling human behavior are insufficient to drive effective study of human cognitive performance or to provide sufficiently rich behavior sets for training applications.

The human behavior representation (HBR) research community has made progress towards meeting the challenge of providing significantly more realistic models of human decision-making behavior and performance within many military operational contexts. A number of HBR modeling efforts are underway, and a series of established models are readily available, including ACT-R, COGNET, Soar, and SAMPLE. Pew and Mavor (1998) provide a good summary of each of these modeling approaches:

Atomic Components of Thought (ACT-R): ACT-R is a hybrid cognitive architecture which represents both declarative knowledge via scheme-like structures, and procedural knowledge via production rules. Its most distinctive characteristic is its focus on learning through experience, and several learning mechanisms are provided for within the architecture (Anderson & Lebiere 1998).

COGnition as a NEtwork of Tasks (COGNET): COGNET is a framework for creating and exercising models of human operators in primarily cognitive tasks. Its intended application is to support the development of intelligent interfaces for operators working in complex environments. It does not provide any modeling of psychomotor behavior. The base assumption of the model is that humans perform multiple tasks in parallel at any given time. COGNET implements the parallel multi-tasking model through rapid attention switching between concurrent tasks (Zachary, Ryder & Hicinbothom 1999).

Soar: Soar is a symbolic cognitive architecture that implements goal-oriented behavior as a search through a problem space and learns the results of its problem-solving. It is used to model the cognitive capabilities of an intelligent agent through a production rule-based approach that embodies procedural, declarative and episodic knowledge. Soar has a full suite of support tools to assist in editing, tracing and debugging developing models (Newell 1990).

Situation Awareness Model for Pilot-in-the-Loop Evaluation (SAMPLE): SAMPLE is a domain-independent architecture for modeling situation awareness (SA) centered decision-making in high-stress, time-critical environments. It provides a hybrid computational architecture to model individual cognitive processes of information processes (via fuzzy logic), situation assessment (via Bayesian reasoning), and procedurally-driven decision-making (via expert systems) (Mulgund et al. 2000).

1.1 Strategies for Integrating Human Behavior Models within Military M&S Environments

The integration of these HBRs within large-scale military simulation environments poses many technical challenges, however. There are fundamental software engineering challenges that are currently being tackled through several efforts, most prominent among them the development and distribution of the High-Level Architecture (HLA) `<https://www.dmso.mil/public/transition/hla/>` and the Distributed Interactive Simulation (DIS) protocol `<http://www.sei.cmu.edu/publications/articles/arch-dist-int-sim.html>`. While these are important efforts within the M&S community, we believe that they are being effectively addressed, and therefore, are not the focus of this paper. Rather, we focus here on some of the more esoteric challenges associated with the integration of high fidelity HBR models within large-scale M&S environments. These challenges highlight the added thought and effort required to effectively match a given HBR model with a specific M&S tool to address a given problem. The issues we will specifically discuss within the scope of this paper are as follows.

Entity Resolution: Selecting the appropriate level of modeling resolution to apply to a given simulation application is an art in and of itself, especially considering the large number of entities operating in a large-scale engagement level simulation. Weighing the cost in terms of computational performance against the benefits of high fidelity behavior modeling can be very difficult. However, it is rarely the case that all of the modeled entities in a given simulation must be represented with significantly high fidelity. Rather, only a subset of entities may require significant modeling detail (e.g., those entities with which a trainee specifically interacts). If we can develop a reliable mechanism by which to load a simulation with some set of nominally “lower” fidelity models, and dynamically replace those models with high fidelity models throughout simulation execution as appropriate, we could provide an efficient way to manage this performance versus modeling fidelity trade-off. We will present an option to accomplish this dynamic entity resolution in section 2.

Variability in Simulated “Sensed Data”: It is rarely the case that a given simulation environment will provide exactly the right level of data resolution and appropriate data representation to drive high fidelity HBR models. Therefore, there is often a “translation” function that must be performed to aggregate simulated data sources into appropriate data packets to drive HBR models. This is usually supported by custom data translations serving the integration requirements for a specific HBR model (and instance of that model) operating within a specific simulation environment and scenario. If we can provide a generalized methodology to aid in the development of data translation protocols applicable across a range of HBR models and simulation environments, we could reduce the costs associated with HBR integration by easing the development process. We discuss an approach to support such generalization in section 3.

Variability in Simulated “Control Data”: Along with variability in the level of detail in sensed data provided by a given simulation tool, there is also significant variability in the level of “control” that that given HBR model will be able to exert on a simulated entity. Some models will be directly “injected” into a simulation in place of a human player (e.g., replacing a human pilot flying a simulated aircraft through a pilot/vehicle interface). In these cases, the HBR must generate very low-level commands (e.g., stick and throttle control). In other cases, the HBR may only have to generate high-level commands, and the simulation environment may translate those into low-level controls (e.g., the HBR generates a flight path and the simulation manages the flight controls to follow that path). In section 4, we describe an approach to generalizing HBR development concepts to support this range of control requirements.

The remainder of this paper discusses these issues in further detail and provides example solutions that we have applied to address them across a range of human behavior modeling applications.

2 DYNAMIC ENTITY RESOLUTION

Most large-scale battlespace scenarios involve many entities representing individual human players or groups of decision-makers. However, specific analysis and training scenarios may only require that a subset of those entities be modeled at a particularly significant level of detail. Modeling all entities in full detail obviously increases the computational load for the integrated simulation system, so it is in the best interests of performance to only model each entity at the level of detail necessary for the given application. But, it is not always known *a priori* which entities must be modeled in detail and which are extraneous to the purposes of a given experiment or training scenario.

For example, as a human-in-the-loop (HIL) trainee moves through a simulated exercise, he/she will likely only interact *directly* with a subset of the modeled entities in the scenario. It is important that these entities be modeled with sufficient detail to effectively react to the unpredictable behaviors of the trainee in order to present a realistic scenario, and therefore, a positive training result. But, it is not known prior to run-time which entities the trainee may encounter directly, and therefore, which entities must be modeled at a higher level of resolution.

As a result, it is often useful to allow for the dynamic adjustment of entity resolution at run-time. This can be accomplished by implementing a separate process within the HBR integration architecture that monitors the scenario as it plays out and identifies when it is appropriate to override the default behavior engines within the simulation with the high fidelity behavior provided by the HBR.

In a recent NASA-sponsored program, we developed a suite of agent-based models to represent commercial pilot, air traffic controller, and airline dispatcher behavior to support the investigation of advanced concepts for distributed air traffic management policies and procedures for future airspace control (Harper et al. 2002). This involved the injection of HBR models within a very large-scale simulation environment, where we were interested in modeling all the air traffic within a large airspace through several hours of air traffic operations. Had we attempted to model all the airspace users with high fidelity models, we would have unnecessarily created significant computational performance issues. However, we were specifically interested in the distributed decision-making processes that could be applied to solve potential air traffic conflict situations and weather avoidance issues that arose through a given scenario. Therefore, it was only relevant to model those entities that were actually involved in a potential conflict or weather avoidance situation with detailed HBR models. The remaining players could be modeled with simple scripts that followed pre-defined flight plans.

We approached this problem by developing a *Management Agent* within the integrated solution, as shown in Figure 2-1. The purpose of the Management Agent was to monitor the air traffic situation and determine (through the use of a very coarse, and therefore, computationally inexpensive, conflict detection algorithm) when specific aircraft might be involved in potential conflict situations. Upon detecting a potential problem, the Management Agent would dynamically instantiate high-fidelity SAMPLE models to represent the pilot, his associated airline dispatcher, and any air traffic controllers that might be involved in solving the potential problem. These agents would then carry out a significantly more detailed analysis of the problem, and implement a sophisticated distributed decision-making process to solve it. Once the Management Agent detected that the problem had been solved, it would delete those agent-based models, allowing the simple behavior engine within the simulation to once again take control of the aircraft.

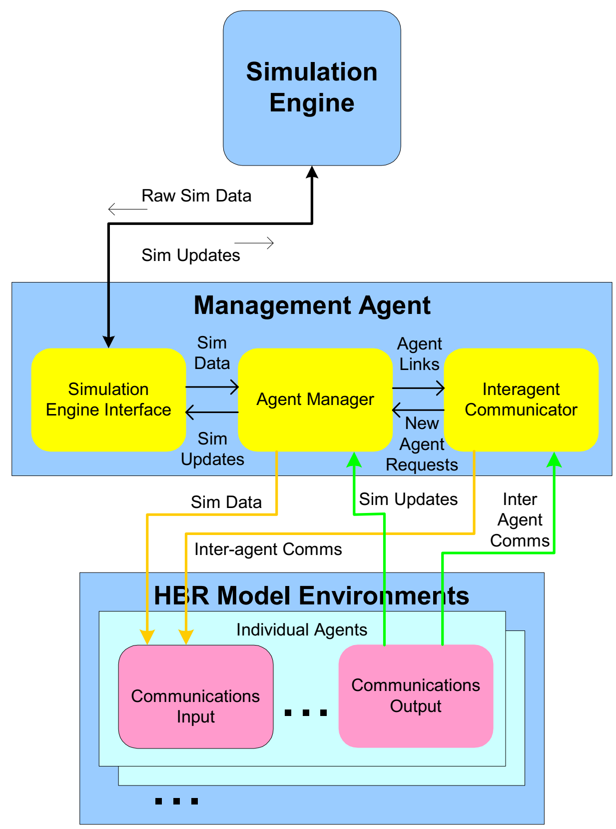

Figure 2-1: Managing Dynamic Entity Resolution

The Management Agent consists of three components, including the Simulation Engine Interface, the Agent Manager, and the Inter-Agent Communicator. The Simulation Engine Interface provides the main communications entry and exit point between the simulation and the HBR modeling environment. The Agent Manager component then determines when agents are needed. When a situation arises that requires an agent instance of a particular HBR model to be created, it will dynamically create and initialize a SAMPLE agent to represent that entity. While the agent instances are active, the Agent Manager component communicates all required simulation data to them, and acquires simulation update information from them to communicate back to the Simulation Engine through the Simulation Engine Interface. Finally, the Inter-Agent Communicator component manages the communications between different instances of SAMPLE HBR models. When entity models need to communicate information, this component ensures that those communications get forwarded to the correct agents, or, if required agents have not yet been created, informs the Agent Manager component to create them. As a result, a SAMPLE agent is not limited to interacting only with other agents that the Agent Manager has deemed fit to generate, but can also force the generation of agents with which it chooses to interact.

3 VARIABILITY IN SIMULATED SENSED DATA

HBR models are driven by simulated "sensor data" generated by the simulation environment. For example, if we were to build a SAMPLE-based model of an air combat pilot, then we would be interested in collecting cockpit sensor data (e.g., track data generated by a simulated radar system) and radio communications to drive the HBR model. If we were interested in a building a simulated soldier model, on the other hand, we might be interested in a collection of state data associated with "currently visible" entities within the combat simulation. It is rarely the case that there exists a direct mapping of simulation-generated data that is readily accessible to the HBR for cognitive processing. At the very least, there is generally some simple data translation to map simulation-generated data into the "language" of the HBR. But sometimes, more significant pre-processing of simulation data is required before passing it into the HBR. For example, a small unit combat simulation will often only provide "truth data" regarding entity state (e.g., position and orientation). That data would then need to be pre-processed to filter out the data outside the modeled soldier's current field of view. Some HBRs may provide a vision model to do this, while others may assume that capability exists on the simulation side.

We cannot provide a general computational tool that is guaranteed to match data effectively between the simulation and HBR in all cases. However, we can provide a framework that can help identify these data mismatches and guide the implementation of "data translators" (e.g., HLA Federated Object Models (FOMs)) in a manner that will support a broad range of HBR models. To do this, we can leverage the commonalities between HBR models in terms of their shared concepts of human cognitive behavior, since they all act on some representation of "knowledge" within a given operational domain. This knowledge may include events of interest, perceived states or beliefs, and selected actions. If we can generate a common set of concepts that define the required "inputs" to HBRs in general, then that framework can be leveraged to generalize the data-level interfaces between the HBR and simulation environment, thus simplifying the integration process.

Our approach to the specification of this common framework is rooted in an ontology of cognitive processing associated with skilled human decision-making behavior that we are currently developing under an ongoing ONR-sponsored effort (Napierski, Young & Harper 2004). An ontology is "a specification of a conceptualization" (Gruber 1993), which provides an abstract model of a particular field of knowledge. It describes a hierarchy of concepts, attributes of concepts, and the relationships between concepts. Our developing ontology describes the concepts associated with cognitive decision-making processes (i.e., abstract representations of events, states, and responses) and the relationships between those concepts.

Figure 3-1 shows a high-level overview of our developing ontology of human decision-making behavior. There are common elements of cognitive theories and architectures captured by the ontology, namely cues, situations, actions, goals, and behavior moderators. Furthermore, there are identifiable relationships between these elements. For example, the goal structure has a predictable effect on selected actions (actions that support current high priority goals will be executed while other actions may not). The ontology also incorporates further decomposition of high-level elements. For example, the class of behavior moderators can be further decomposed to represent different effects of personality traits, affective state, and physiological factors. Furthermore, the base ontology can be extended into a given domain (as indicated by the grey overlays). A model developer can extend the concepts into a domain-specific ontology, and use the concept of "inheritance" to maintain the relationships of the common ontology within the more specific domain ontology.

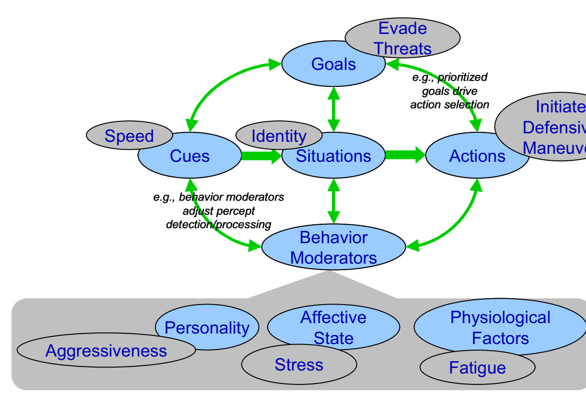

Figure 3-1: Common Ontology of Human Decision-Making

How does this framework lend itself to the simplification of simulation/HBR data interfaces? If a given HBR model can classify its data requirements within this framework, extending it effectively to represent domain-relevant data that must be collected from the simulation environment, then those data requirements can be easily "published" to support simulation integration. The resulting data requirements will include sufficient context to enable more straightforward interpretation by the simulation integrator, thus simplifying the integration process.

4 VARIABILITY IN SIMULATED CONTROL DATA

In section 3, we dealt with the variability in simulation data defining *inputs* to integrated HBR models. Here, we discuss similar issues associated with matching *outputs* from the HBR to control the simulated entity. The common ontology classifying the primitives associated with human decision-making is certainly relevant to matching output control actions between the HBR and simulation as well. However, there are additional complexities associated with the control side of HBR integration. Specifically, the level of control exerted by an HBR model may vary significantly from one simulation environment to another. For example, one air combat simulation may require low-level stick and throttle commands to control the simulated aircraft, while another simulator may only require high-level control where the HBR might generate a flight path and the simulated aircraft system may actually generate the low-level commands to follow that flight path.

In the cases where the simulation requires low-level control input and the HBR tends to focus on high-level decisions (as is the case with most cognitive architectures, including Soar, ACT-R, and SAMPLE), it is important to separate the high frequency control loop from the low frequency reasoning loop. It is often sufficient to run the HBR reasoning algorithms at approximately 1Hz, while the underlying control algorithms should be run at a minimum of 10Hz to generate effective real-time control of the simulated entity. Therefore, we recommend an architectural separation between these two components when real-time motor control is required by the HBR.

Under a USAF-sponsored program to develop tactical air combat pilot agents (Mulgund et al. 2000), we developed a Pilot Decision Logic (PDL) module for defining combat pilot behavior within an air-to-air tactical engagement scenario in the MIL-AASPEM simulation. The integration of the PDL module within the MIL-AASPEM architecture is shown in Figure 4-1. The simulation, which includes high fidelity representation of the vehicle and its onboard systems (radar, weapon systems, etc.), sends state information and target track data to the pilot agent (in the PDL) via the Realist module, which performs an interpretive function between simulated entity and PDL. The PDL performs the information processing, situation assessment and decision-making functions (within SAMPLE) and sends pilot assignment commands back to the simulator. In this situation, we have a mismatch between commands generated by the agent and those implemented by the vehicle model within the simulation. The PDL defines pilot assignments such as "perform evasive maneuver" to indicate the type of maneuver to be applied. This assignment is sent to MIL-AASPEM's Realist module, which carries out an interpretation function of "perform evasive maneuver" to derive the actual control inputs (stick and throttle commands) that the simulation's vehicle model will implement to perform the maneuver. Essentially, the PDL defines *what to do* and the Realist model defines *how to do it*.

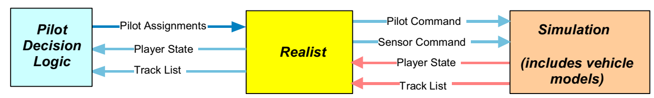

Figure 4-1: MIL-AASPEM Architecture

If a target simulation environment does not provide a Realist-type module to perform this translation of high-level behaviors into low-level controls, then the HBR integration architecture should provide this same separation of control structures.

In a previous program (Harper, Ho & Zacharias 2000), we mimicked the Realist functionality for the urban operations domain, where we integrated a SAMPLE-based model of individual soldier behavior with Boston Dynamics' DI-Guy model `<http://www.bdi.com/html/di-guy.html>`. The physical DI-Guy model responds to simple commands that direct its motion within the simulated environment. These commands consist of a state command (e.g., stand, walk, run, crawl) as well as position, velocity and orientation information to portray the entity within the simulation. DI-Guy can also follow a specified path through the simulated environment, while carrying out particular actions defined through the API (e.g., programmed hand signals, etc.). However, our SAMPLE-based soldier agent controlled DI-Guy's behavior at a much higher level of abstraction, producing commands such as "perform serpentine maneuver" to direct DI-Guy to traverse a hallway, for example. Therefore, the integration of the SAMPLE agent with the physical model required an additional component to interpret the meaning of "perform serpentine maneuver" in terms of a path and DI-Guy action calls that were meaningful to the physical model. This translation was accomplished through the development of a *Command Interpreter* module, which consisted of an Expert System (ES) knowledge base defining agent-produced "behavioral commands" in terms of DI-Guy "physical commands".

The functionality of the Command Interpreter is directly analogous to that of the Realist in MIL-AASPEM. Our soldier agent defined what to do (e.g., perform serpentine maneuver) and the Command Interpreter defined how to do it by deriving DI-Guy inputs of state, velocity and path definition that resulted in the soldier model moving through the building in a serpentine maneuver.

Consider the example of a team of infantry soldiers performing a room clearing operation. There are set, well-trained procedures for carrying out this type of task (Department of the Army 1979). Figure 4-2 shows the path to be taken by the lead man in carrying out a search of a room in such an operation. Upon entering the room, he checks the front corner in the direction of entry. He then rotates 90° to check the rear corner. He then begins to move along the side wall to the rear corner, rotating his field of view towards the other rear corner as he moves. By the time he reaches the back corner, he should be facing the point of entry. Throughout this procedure, if the soldier recognizes a potential target, he must evaluate whether it is a combatant or noncombatant contact, and only fire his weapon upon identifying the contact as a threat.

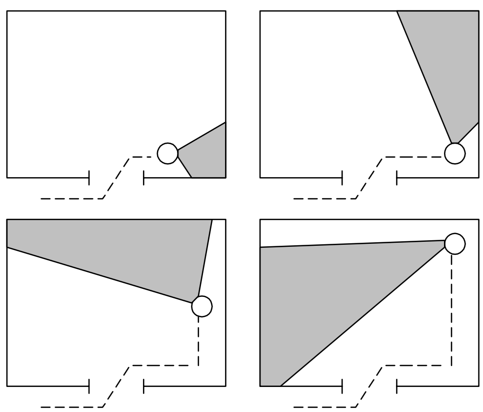

Figure 4-2: Path of Number 1 Man in Room Clearing Task

Our soldier model carried out this procedure as follows:

- The SAMPLE-based soldier agent produces a command to enter and search the room.
- The Command Interpreter translates this command, according to the trained procedure and the physical characteristics of the environment, into a set of state and path point commands for the DI-Guy model to follow. These points identify the position and orientation of DI-Guy throughout the search procedure.
- As DI-Guy moves through the room, the simulator continues to send state information to the agent to be processed. The agent applies its perception model to search the room and trigger contact events upon finding a potential target.
- The agent then enters a target identification phase to establish the potential threat posed by the contacted entity.
- If the contact is identified as a hostile threat, then the soldier agent sends a command to fire on the target back to DI-Guy.
- The Command Interpreter then derives the DI-Guy commands to fire on the target, producing physical commands identifying location, orientation and firing stance position.

By effectively separating the low frequency reasoning process from the high frequency control loop, we are able to minimize the performance lag for real-time control since it can continue to process until the reasoning engines within SAMPLE generate new high-level directions. Had these two processes been fully integrated, then there is a much higher risk of unresponsive motor control generating delayed responses within the simulation engine.

5 CONCLUSION

The application of advanced M&S tools to a range of analysis and training functions throughout the DoD requires significantly more focus on the integration of high fidelity models of human decision-making behavior. The HBR community offers a number of computational modeling solutions to meet this need, but there are many challenges to the effective integration of these models within the full range of military simulation tools. Here, we have attempted to highlight some of the challenges that we have faced through several years of integrating HBRs within simulation environments, and offer some advice to support these efforts based on our experience.

REFERENCES

Anderson, J. R., & Lebiere, C. 1998. *Atomic Components of Thought*. Hillsdale, NJ: Erlbaum Associates.

Department of the Army 1979. *FM 90-10: Military Operations on Urbanized Terrain (MOUT)* (FM 90-10)

DMSO. 2000. *Proceedings of the Ninth Conference on Computer Generated Forces and Behavioral Representation*, Orlando, FL.

Gruber, T. R. 1993. A Translation Approach to Portable Ontology Specification. *Knowledge Acquisition*, 5(2), 199-220.

Harper, K., Guarino, S., White, A., Hanson, M. L., Bilimoria, K., & Mulfinger, D. 2002. An Agent-Based Approach to Aircraft Conflict Resolution with Constraints. *AIAA Guidance, Navigation, and Control*, Monterey, CA.

Harper, K. A., Ho, S. S., & Zacharias, G. L. 2000. Intelligent Hostile Urban Threat (IHUT) Agent for MOUT Operations. *9th Conference on Computer Generated Forces and Behavior Representation*, Orlando, FL.

Mulgund, S. S., Harper, K. A., Zacharias, G. L., & Menke, T. 2000. SAMPLE: Situation Awareness Model for Pilot-in-the-Loop Evaluation. *9th Conference on Computer Generated Forces and Behavioral Representation*, Orlando, FL.

Napierski, D. P., Young, A., & Harper, K. A. 2004. Towards a Common Ontology for Improved Traceability of Human Behavior Models. *2004 Conference on Behavior Representations in Modeling and Simulation*, Arlington, VA. SISO.

Newell, A. 1990. *Unified Theories of Cognition*. Cambridge, MA: Harvard University Press.

Pew, R. W., & Mavor, A. S. 1998. Modeling Human and Organizational Behavior: Application to Military Simulations. *National Academy Press*.

Zachary, W., Ryder, J. M., & Hicinbothom, J. H. 1999. Cognitive Task Analysis and Modeling of Decision-Making in Complex Environments. In Cannonbower & Salas (Eds.), *Decision Making Under Stress: Implications for Training and Simulation*. Washington D.C: American Psychological Association.

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