Imperfect Situation Awareness: Representing Error and Uncertainty in Modeling, Simulation & Analysis of Small Unit Military Operations

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ABSTRACT: *This paper examines the use of agent-based modeling and simulation to represent Situation Awareness/Situation Understanding (SA/SU) and its antithesis, the so-called "fog of war". "Good SA/SU focuses on support for "the right information, for the right person, at the right time." As a consequence, measuring improvements in SA/SU will require comparison to baselines of "wrong information, wrong person, wrong time." Unfortunately, current M&S tools are most generally characterized by model omniscience; individual entities typically "recognize" friend from foe, "know" the precise location, speed and heading of themselves and their targets, and, most importantly, act in accordance with this knowledge. Such omniscience is, of course, at considerable variance with the uncertain, incomplete, inconsistent, and often erroneous data that constitute the "fog of war" in actual operations. The intent of this paper is not to add materially to the theory of SA/SU, but rather to develop an engineering solution to the problem of representing imperfect SA/SU in agent-based simulations of small unit operations.*

1 Introduction

In the late 80's and early 90's the "soldier as a system concept" (now referred to as the more encompassing "warrior system")[1] was developed to forge the individual combatant and his equipment into a complex, synergistic, system of systems. This warrior system concept has been widely accepted internationally[2], and today focuses on integrating the capabilities of new C4ISR[3] technologies to improve individual and unit situation awareness and situation understanding (SA/SU).[4] At present, however, Modeling & Simulation (M&S) of military operations suffers from inadequate representation of SA/SU and decision-making, and therefore M&S-based analysis lacks the tools to assess potential SA/SU improvements provided by new technologies or proposed systems[5].

As an example, "good" SA/SU technologies should help to provide "the right information, for the right person, at the right time." Consequently, measuring SA/SU improvements will require comparison to baselines of "wrong information, wrong person, wrong time." Unfortunately, current M&S tools do not consider such baselines. These tools are characterized by model omniscience; individual entities "recognize" friend from foe, "know" the precise location, speed and heading of themselves and their targets, and act in accordance with this knowledge. Such omniscience is, of course, at considerable variance with the incomplete, inconsistent, and often erroneous data that constitute the "fog of war" in actual operations.

1.1 Objective of the Paper

This paper examines the challenge of representing SA/SU and its antithesis, the so-called "fog of war",

[1] See for example [Middleton & McIntyre 2001]

[2] For example, [Housson 2008] discusses programs by the British: FIST (Future Integrated Soldier Technology), Germans: IdZ (Infanterist der Zukunft), Spanish: COMFUT (COMbatiente FUTuro), French: FELIN (Fantassin à Équipements et Liaisons Intégrés), and Italians: Soldato Futuro. See also [Leuw, 1997], [HassgÂrd, 2002], [Curtis, 2002], [Hobbs, 2000], [Underhill 2009] for Dutch, Swedish, Australian, and Canadian examples and perspective.

[3] Command, Control, Communications, Computers, Intelligence Surveillance and Reconnaissance

[4] Rather than engage in a discussion as to the differences between SA and SU, I choose to blur them together to a single over-arching concept following the pragmatic definition of [Adam 1993] "knowing what is going on so I can figure out what to do"

[5] See for example [Tollefson et.al 2008], [Middleton & Mastroianni 2008], [Pew & Mavor 1998]

through the use of agent-based modeling (ABM) and simulation. My focus is on the warrior system, small unit operations and irregular warfare. My goal is to develop a framework for enhancing ABM SA/SU capabilities. The framework will define agent functions and data structures to: 1) reflect the uncertainty and error in what agents know; 2) represent how they act on that knowledge, and 3) capture metrics that correlate levels of SA/SU with operational outcomes.

I am not looking to develop a new theoretical understanding of SA/SU and decision-making. Rather my goal is an engineering solution to the practical problems faced by decision-makers and the analysts who support them. The solution must support system design requirements and evaluation of the technological approaches that may be proposed to meet those requirements. The solution should facilitate the exploration of tactics, techniques and procedures (TTPs) for the employment of current and proposed new systems. Making the distinction between fidelity and resolution expressed by [Bailey & Kemple 1992], the solution should focus on improving model fidelity, with minimal increases in model resolution, level of detail or complexity.

1.2 Problem Statement

Systems analysis of large weapon systems (e.g., manned vehicles and airplanes) is supported by engineering models that describe and predict the operation of these systems. Such models are generally characterized by deterministic, Newtonian physics-based representations of closed systems, i.e. systems whose exchanges of mass and/or energy with their environment are constrained to a relatively few, well-known, factors. These models may incorporate stochastic treatment of systems performance, based on statistical data from measurement of well-defined systems' functions. Their model parameters span the analytically relevant/interesting areas of the problem space, and there is essentially a one-to-one mapping between model features and systems' functions. These features support model verification and validation based on theoretical concepts, and supported by empirical data on operators/systems' performance.

I maintain the problems of warrior systems' analysis begin with the statement, "**we lack an engineering model of the individual soldier.**" The complexities of the warrior system are not amenable to the strict reductionist approach of orthodox systems analysis, which fails to account for the dynamic and highly non-linear interactions of the cognitive and physiological elements that constitute the warrior system. These complexities are exacerbated further by the nature of irregular warfare and asymmetric combat, in which the interactions between friendly forces, adversaries, and neutrals form a seemingly chaotic dynamic landscape.

Writing for the Military Operations Society's Phalanx in 2002, Vincent Roske[6] spoke of the need for new tools to address the class of "open systems" not accessible using traditional operations research tools. Such systems are characterized by uncertainty and imprecision in both system inputs and system behaviors, which can make their behavior harder to predict. At the same time, embracing the uncertainty and non-linearity of these systems can provide much higher fidelity in describing the performance of systems whose subsystem capabilities can, and often do, lead to the whole being greater than the sum of its constituent parts.

We need to upgrade our concept of "engineering" models. We need engineering models that allow us to explore virtual systems whose behaviors emerge from general rules of operation, that are not limited to functional capabilities that can be reduced to physics-based algorithms. This upgraded concept does not mean eliminating the use of physics or the other "hard" science, it simply means extending the reductionist approach to support a wider variety of systems decompositions. It means, for example, decomposing systems operations into sets of entity or object interactions as in done in agent based models. Ilachinski describes this approach as collectivism:

Collectivism embodies the belief that in order to properly understand complex systems, such systems must be viewed as coherent wholes whose open-ended evolution is continuously fueled by nonlinear feedback between their macroscopic states and microscopic constituents. It is neither completely reductionist (which seeks only to decompose a system into its primitive components), nor completely synthesist (which seeks to synthesize the system out of its constituent parts but neglects the feedback between emerging levels).[Ilachinski 1996]

This complex systems approach also suggests the need to measure the "validity" of simulation outcomes as less in terms of their agreement with predictions of real world phenomena, and more in terms of their ability to provide insight and to further our understanding of these phenomena.

2 Approach

The above considerations suggest agent-based models that view military operations as complex adaptive

[6] Roske was then serving under the Chairman of the Joint Chiefs of Staff as the Deputy Director, J8 (Wargaming, Simulation & Analysis)

systems (CAS)[7] provide a promising approach for analysis of SA/SU issues.

Under this approach, simulated "Intelligent" agents (IA) make decisions and attempt to satisfy mission goals according to their own individual (and probably imperfect) SA/SU. While any simulation maintains its internal "ground truth" knowledge base, each IA will have a "perceived truth" knowledge base – the idiosyncratic view of the combat situation, as seen by that individual IA and obscured by the agent's local "fog of war". IA behavior choices are made on "perceived truth" of the agent; the behaviors and their effects, however, take place in the "ground truth" world of the simulation.

Allowing each agent to act on an imperfect worldview supports evaluation of the operational costs of uncertain, incomplete and/or incorrect information. It also supports explicit modeling of leader decision-making processes based on such data, of imperfect command and control, and/or imperfect subordinate receipt of and subsequent execution of orders. Such modeling is critical if we are to estimate the benefits of proposed new or modified systems, and/or adjustments to tactics, techniques and procedures.

This approach supports measures of command and control such as the Objective Information System Assessment (OISA) Paradigm [Davidson, Pogel, and Smith, 2008], which compares the performance of individual decision-makers employing a particular information system, to what that same decision-maker would have produced given an alternative data stream.

2.1 ABM as an Engineering Model of the Warrior System

In addition to all of the physics-based phenomena characteristic of military operations, an engineering model of the Warrior System must also address the so called "soft factors" – morale, leadership, training, and the values/beliefs associated with nationality/ethnicity, that are critical to current operations.

The framework for an engineering model of the individual soldier centered on agent-based modeling has already been established through distillation models such as Pythagoras[8] and CROCADILE[9] and more detailed models such as IWARS[10] and Combat XXI[11]. , with intelligent agents that are:

- goal-oriented - able to build courses of action by taking the initiative to change elements of the world state to desired objectives
- perceptive - able to receive data from their environment, including knowledge of their own state and that of other entities of interest to them,
- active - able to perform actions affecting their environment, and
- autonomous - able to use internal logic to make decisions and initiate behavior sequences based on what is appropriate given the perceived environment.

Agents representing combat forces must also generally be:

- mobile - able to move around in their simulated environment,
- insightful - capable of inferring the intentions of others, determining the desires and plans of other agents, and
- social - able to share goals, cooperate with or coerce other agents.

A key distinction between agents that are "intelligent" and those that are merely reactive is the concept of having "knowledge" of the world based on current and historical data from the agent's sensory input capabilities. Intelligent agents are not omniscient, they do not share the simulation "god's eye" view of the world, rather they gather and interpret data according to their own capabilities. One can characterize the degree of an agent's intelligence based on the extent of its historical sensory database, its capability to use inference to supplement incomplete input data, and/or to resolve uncertain or inconsistent data, and its degree of autonomy. Autonomy is of particular importance for simulation-based analysis, because it is gauged by the degree to which behaviors are not pre-scripted by simulation designers. Autonomy is enhanced by increasing both the number of options available to the agent in response to the perceived environment, and the flexibility the agent has in choosing those options.

Autonomy also permits unpredictable (to other entities) behaviors, a key feature of viewing military small unit operations as CAS. Autonomy makes possible the "adaptive" part of complex adaptive systems, providing the potential for emergent behavior through IA co-evolution with a dynamic operational environment and with other systems. Adaptation is a concept taken from the biological view of evolution and implies the operation of a "fitness" function or functions that support "selection" of those characteristics or behaviors of the system that enable it to best "fit" in its environment. In the warrior systems view, fitness

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[7] See for example [Ilachinski 2004], [Cioppa, Lucas & Sanchez 2004], {Horne & Leonardi 2001]

[8] See for example [Bitinas et. al 2003]

[9] See for example [Easton & Barlow 2002]

[10] See for example [Bachman et al 2008]

[11] See for example [Kunde & Darken 2006]

functions are derived from satisfying IA goals, and "fitter" systems, e.g. those with improved SA, are those which are better able to achieve mission and unit goals.

The IA must derive data from the environment, through appropriate sensory and communications processes. The IA then interprets these data in the context of the its experience and current knowledge base, achieving some level of comprehension as to what the data means, and finally, develops a set of expectations[12] as to the results of its own or other's actions and behaviors. Such expectations play a key role in proposing to view the IA as a basis for an engineering model of the warrior system. Following Klein's (1999 & 2008) concept of Naturalistic Decision-Making (NDM), I see the IA as continually adjusting its behavior based on the degree to which its expectations are or are not met.

2.2 Architecture

The architecture proposed herein basically conforms to Miller & Shattuck's (2004) Dynamic Model of Situated Cognition (DMSC). This model represents the perception of ground truth as a function of sensor systems, the capture of those data by command and control systems, and the (possibly imperfect or erroneous) processing of these data into Endsley's (1995) three levels of SA: perception, comprehension and future projection.

Of course, many of today's models, such as those listed in section 2.1, already represent aspects of SA/SU and decision-making under uncertainty, incorporating aspects of the DMSC and Endsley's three levels of SA. The key to augmenting extant representations is the incorporation of model features that further distinguish between an individual's perceived world view and ground truth. Incorporating these features requires the design, development, and implementation of three inter-related elements:

1. data structures to characterize each entity's perceived knowledge of the operational environment;
2. algorithms and heuristics to populate, maintain, and update those data structures; and
3. inference schemes employing these data to represent operational decisions.

[12] [Kunde 2005] discusses the role of expectations and mental models in his computational model for mental simulation in a combat simulation environment. He proposes a simulation architecture that incorporates the basic ideas of Recognition Primed Decision-making (RPD) [Klein 1993], and decision-making architecture as a framework for applying mental simulation in a combat simulation environment. [Kunde & Darken 2006]

These features can be incorporated into current simulations in a modular architecture following Boyd's OODA loop [Boyd 1986] as shown in Figure 1. In this approach, the three elements are encapsulated in modules that constitute the "Orient" and "Decide" components of the OODA Loop, the blue boxes of Figure 1.

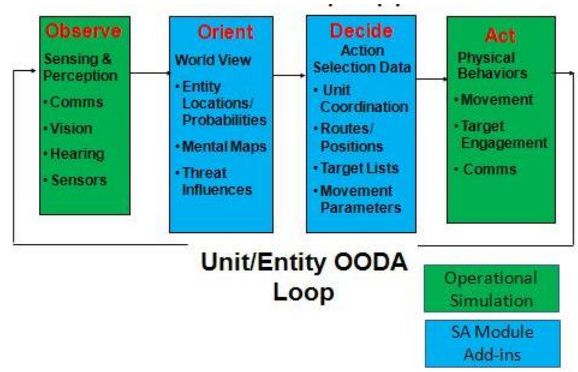

Figure 1 Modular OODA Loop Approach

This approach provides a controlled interface between new SA/SU capabilities and basic simulation processes. The sense/perception processes native to host simulation entities allow those entities to "observe" their virtual world as before, providing data on the simulation environment and the objects in it. The new "orient" modules interpret those data though (potentially imperfect) filters to populate and update world view data structures unique to each entity. As an example, an entity may observe another entity that it previously would have identified according to its force association and any threat value. New "orient" filters could "translate" entity sightings into levels of evidence for associating that entity with a given force or threat intent. Similarly such filters could add imprecision and/or error to the sighting entity's perception of the sighted entity's location. Inference routines could evaluate evidence from multiple sources, resulting in attributes of the sighted entity described as degrees of membership in fuzzy sets as opposed to the generally crisp (e.g., friend or foe, within range, at objective) options currently available.

The "oriented data" is now information that is used by the decision logics of the "Decide" module to choose and direct those entity behaviors deemed most likely to achieve entity/unit goals. The host simulation "Act" capabilities carry out these behaviors and determine effects on other entities and the environment.

2.3 Data Structures

There are three main classes of data structures required under this approach: Perception Data Structures (PDS), Inference/Decision Structures (IDS) and Behavior Data Structures (BDS). The role these structures is to capture the results of filtration and fusion to support inference/decision procedures not necessarily native to the host simulation (PDS), to provide the parameters and inter-object relationships needed by these inference/decision procedures (IDS), and to translate the results of these procedures into directions consistent with host simulation behaviors (BDS).

PDS reflect the operational environment and the entities in it as perceived by a given agent, interpreted and formatted as required by that agent's various inference schemes and decision models. They include:

- cues – environmental data, either direct perception or as a result of shared communications, expressed as object state variables;
- alerts – special cues demanding immediate action;
- thresholds – object state variable values that reflect or initiate a state change in that object or others;
- landmarks – cues that cannot be ambiguously interpreted. Recognition of a landmark either absolutely confirms or refutes elements of an IA's currently held world view associated with that landmark; and
- influence ambits – an area, range or scope over which an object can/does exercise control.

IDS provide the framework and core parameters of the schema used to represent inference[13] and/or decision-making. Examples include:

- patterns for situation assessment and projection heuristics representing mental simulation - needed for recognition-primed decision-making[14];
- directed acyclic graphs (DAG) and associated conditional probability distributions – needed for Bayesian belief networks[15];
- causal weighted adjacency matrices- needed for fuzzy cognitive maps[16];
- a basic probability assignment function (bpa), a Belief function (Bel), and a Plausibility function (Pl) – needed for Dempster-Schaefer theory[17];
- belief sets and belief states, goal sets and goal states, and plan sets – needed for the Belief, Desire, and Intentions (BDI) paradigm[18]; and
- directed graphs representing input, output and hidden layers of artificial neurons and weighted connections – needed for neural networks.[19]

BDS allow the new orient and decide modules to share data about the problem space with native behaviors. They are the vehicle by which IA decisions are shared with the host simulation. There are three basic forms:

- Course of Action options;
- Behavior parameters - targets and target priority lists, types and rates of fire, shoot/no shoot decision thresholds for engagement; routes and waypoints or direction vectors for movement, speed and movement formations; and
- Communications – Situation reports (SitReps) to other units, especially command units, directives to subordinates, unit coordination, request for fire or other support.

Taken in concert, these structures and the inference/decision schemes they support can address some significant shortfalls in current simulation capabilities. For example, current models generally require an acquired sight picture of a target entity as a prerequisite to firing a weapon. There is little capability for behaviors such as firing at sound cues, "leading" a moving target, suppressive fire at locations with no visible targets, or more rapid acquisition of a target based on previous detection history.

2.4 Inference and Decision-Making

Decision-making is frequently looked at as a discrete event, with alternatives considered, a choice made, and that choice acted on. In the world of discrete event simulation this view is certainly justified at some level, even continuous processes are broken into atomic chunks of activity, and the scheduling of the next event represents a decision of some sort. I believe, however, that it is useful to consider decisions as falling into three broad, albeit overlapping, categories:

- prescriptive plans, e.g., course of action selection, scheduling and coordination of entity/unit tasks, macro-level movement parameters (route selection in terms of general destination, waypoints, avenues of advance, etc.)
- reaction to unanticipated events, e.g., correction of meso-level movement (adjust next waypoint to detour around obstacle/threat, modify formation), engage an adversary/ choose engagement tactics, call for fire or request other kinds of support; and

[13] Following the general lead of [Davis, Shrobe & Szolovits 1993] I am using inference in the generic sense as a way to get new information from old, rather than as limited to sound logical inference.

[14] See for example [Klein 1993] or [Warwick et.al. 2001]

[15] See for example [Russell & Norvig 2003]

[16] See for example [Kosko, 1986]

[17] See for example [Sentz & Ferson 2002]

[18] See for example [Kinny, Georgeff &Rao 1996]

[19] See for example Rao & Rao 1993]

- repeated and/or continuous modification of combatant behavior parameters, e.g., micro-level movement (how fast to move, in what direction, fine-tune selection of cover or firing positions), choose which targets to engage when, adjust aim points and rates of fire.

There are a wide variety of approaches to representing and/or facilitating decision-making, some of which are illustrated in Figure 2, and are supported by the IDS examples listed above.

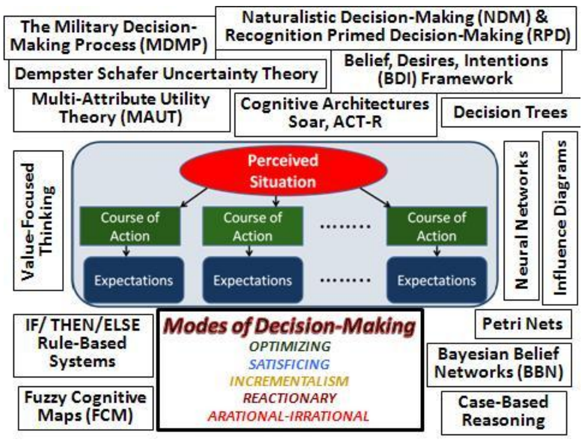

Figure 2 Decision Approaches

Central to all of these paradigms/architectures/ methodologies is the view of a decision as the selection of "doing something"- a course of action, based on an understanding of the current situation – an individual's perceived SA/SU, and with projected outcomes – expectations, associated with each potential course of action.

Also common to these approaches is the concept of rational action, that the decision-maker will attempt to find the "best" course of action to achieve his/her goals. Figure 2, however, also lists the modes of decision-making from [Zim, 1999], which correlates the effects of time pressure and stress to the quality of decision-making. Zim describes a number of problems observed in decision- makers under stress, including:

- changing from deliberative to reactionary modes;
- relying on only a limited fraction of available information with a bias towards that which is familiar and corresponds to earlier perceptions over that which is relevant and/or unexpected;
- making more mistakes but being less likely to acknowledge them; and
- increasing micro-management of subordinates.

Representing these tendencies towards "imperfect" decision-making is critical to providing a robust simulation test bed for SA/SU technologies. Integrating more of the above "rational" decision approaches (or combinations thereof) into current simulations, is a necessary, but not sufficient condition for robustness, such integration must be accompanied by realistic representation of error and imperfection.

Error and uncertainty can be introduced, for example, by following Miller and Shattuck's concept of multiple lenses for acquisition and understanding of ground truth data with those lenses dynamically warped as appropriate to degrees of stress and time constraints.

Error and uncertainty also play a big part in the feedback loop between expectations and decisions to adjust or change behaviors. Expectations may not be met because of failure to understand the decision context (flawed SA/SU), because of unpredictable random variations in physical processes, and/or systemic error in the decision process itself (invalid logic, erroneous antecedent/consequent connection or other incorrect schema elements).

2.5 Implementation Issues

For many current simulations initial integration/ implementation of new SA/SU features can begin without needing "new" data. By using the data structures described above, and using data filtration, data fusion and inference simulation entities can explicitly recognize information already implicit in the simulation environment. For example, consider a scenario in which a small unit has detected and attempted to engage a number of adversaries who are taking advantage of local terrain for cover and concealment. By adding new data structures to record a shared unit history of detections and positions, an inference scheme such as a Bayesian Belief Network could conclude that the size of the adversary unit was too great for the engaging unit and develop a "call for fire" message, assuming that the host simulation supports indirect fire missions. Alternatively, if the adversary force is more manageable a BDS could post artificial "targets" on a target priority list. These targets, when engaged with host simulation firing behaviors, would have the effect of suppressive fire, enabling the engaging unit to close with and defeat the adversary force.

Augmenting the host simulation with additional scenario data and/or new behaviors would further expand the utility of this approach. For example, the addition of terrain characteristics with semantic content, i.e. operationally relevant meaning, can enhance the representation of engagement behaviors such as those described above. For example if doors or windows are understood to be objects where entities can enter or leave buildings, they become candidates for suppressive fire. Explicit inclusion of soft factors such as morale, unit cohesion, and training could also play an important role in the representation of suppression and other reactive behaviors.

These features do not come without cost; clearly keeping each entity's unique world view will increase simulation memory requirements. Furthermore, capturing the dynamic nature of complex systems relationships will require maintaining a history of entity perceptions and other state variables that will further increase memory requirements. The persistence of these data, expressed as decreasing validity and/or credibility as a function of time, is not as yet well understood.

Supporting data for defining fuzzy set membership relations or other measures of uncertainty are scarce, and will probably have to be drawn from subject matter experts (SME). Similarly construction of inference schema to supplement incomplete input data, and/or to resolve uncertain or inconsistent data will be supported less by hard data, and rest instead on analysts' judgments and SME estimations.

Adding semantic content to terrain significantly increases the effort required for scenario development. For example, giving goal-driven IA the ability to interpret, and to make better use of, terrain features of military interest, requires the introduction of a complex set of terrain attributes. These attributes would capture such features as: Observation and fields of fire, Avenues of approach, Key and decisive terrain, Obstacles, and Cover and concealment[20]. Linking observed features of terrain with known enemy tactics and tendencies would further allow intelligent exploitation of terrain, with dynamic definition of areas of immediate importance, danger areas, choke points, and so forth.

Implementation of new features would best be approached in a modular fashion through incremental development. In such development, increasingly more robust versions of each element are implemented through a series of integrated cycles. This approach leads to analytical flexibility and accommodates application requirements for varying degrees of resolution and fidelity. It also supports hierarchal layers of inference and decision-making capabilities to address issues of information sharing among multiple potentially heterogeneous problem sets, as for example when an agent may need alternatives to support a "fight or flight" response. Different and possibly competing inference schemes can suggest potential targets and routes for retreat as the overall problem is parsed into independent parts. The end-result is a flexible data-directed process that allows problem solutions to compete based on different criteria dependent on the situation, the current state of the agent and its active goals.

The incremental approach also helps address issues of model validity. By its very nature, any representation of the human dimensions of error, uncertainty and imprecision lacks the first principles models of cause and effect that are the foundation of "validated", physics-based models and simulations. Such representations can still fall under the purview of scientific rigor, but there is a need to extend that concept to incorporate a "soft", incremental focus, where parametric analysis bounds regions of factor effects and the extent/significance of functional relationships, and where increasing levels of correlation correspond to increased acceptance of predictive validity.

The bottom line is that the actions of an intelligent agent are taken in accordance with that agent's unique SA/SU and in expectation of fulfilling one or more goals. Using the data structures and inference procedures described above, an agent should be able to compare expectations to observable aspects of the environment. Agent behaviors are then seen as a cycle of updating/correcting SA/SU, followed by modification of behaviors as that new SA/SU suggests, until goals are achieved or a recognized failure point occurs.

Author Biography

VICTOR E MIDDLETON is a Senior Operations Research Analyst with over 30 years experience developing, implementing, and applying mathematical models and simulations for a wide variety of military and civilian studies and analyses. He is one of the principal authors of the US Army's Integrated Unit Simulation System (IUSS), developed by Simulation Technologies, Inc, under contract to the US Army Research Development and Engineering Command (RDECOM) Natick Soldier Center and was the Principal Scientist for the evolution of the IUSS into a new model, the Infantry Warrior Simulation (IWARS), to meet the joint needs of NSC and the US Army Materiel Systems Analysis Activity (AMSAA).

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