Modeling Human Perception of Situation Awareness During Constructive Experimentation

Philip Colon	John Tran, Ke-Thia Yao	Michael Anhalt, Jacqueline M. Curiel
Toyon Research Corporation	Informaton Sciences Institute	Alion Science and Technology
Goleta, CA	Marina del Rey, CA	Marina del Rey, El Cajon, CA
philipc@toyon.com	{jtran, kyao}@isi.edu	{manhalt, jcuriel}@alionscience.com

ABSTRACT

Highly advanced sensor technologies give our military commanders a significant command and control (C2) advantage over our enemies during conflicts, particularly with respect to situation awareness (SA). The use of advanced sensor technology models in synthetic battlespace gives war fighters parallel advantages. Two accepted simulation methodologies for analyzing the impact of sensor technologies are through Human-in-the-Loop (HITL) experiments, such as Joint Urban Operations (JUO), which utilize sensor capabilities to assist human participants during the experiments, and Monte Carlo Constructive (MCC) simulations, which can be used to model human performance. In HITL experiments using Joint Semi-Automated Forces (JSAF), participants describe their SA using Situation Awareness Objects (SAOs) which then can be reconstructed using Endsley's (1995) three levels of SA (perception, comprehension, and prediction). MCC experiments, which are dominated by algorithmically determined behaviors, can be used to model SA. Sensor measurements currently can be fused to perceive individual entities, but do not have the capability to recognize groupings of entities, resulting only in partial perceptual SA. Furthermore, current sensor data fusion models do not produce the second and third levels of SA, comprehension and prediction.

This paper will report research efforts to utilize both methodologies to expand the use of SAOs beyond player declarations to the automatic generation of SAOs. We develop a method to organize events drawn from scenarios taken from HITL experiments using SAOs in order to develop situation awareness algorithms for the MCC runs. These model-generated synthetic SAOs (SSAOs) can be compared to SAOs generated by human players to identify the accuracy of the models as well as be used to identify strengths and weaknesses in player performance.

ABOUT THE AUTHORS

Philip Colon is an Analyst with Toyon Research Corp, supporting the USJFCOM J9 Experiment Engineering Department. He has supported numerous sensor systems analyses and also functions as Toyon's chief software engineer for distributed simulation experiments, including JUO Urban Resolve Phase 1. At Toyon, he focuses on technical analysis, modeling, and simulation of sensors and weapon systems operating in hostile environments. He received a B.S. with honors in Mathematics from the University of California at Santa Barbara.

John J. Tran is a researcher at the Information Sciences Institute, University of Southern California. He received both his BS and MS Degrees in Computer Science and Engineering from the University of Notre Dame, where he focused on Object-oriented software engineering, large-scale software system design and implementation, and high performance parallel and scientific computing. He has worked at the Stanford Linear Accelerator Center, Safetopia, and Intel. His current research centers on Linux cluster engineering, effective control of parallel programs, and communications fabrics for large-scale computation.

Ke-Thia Yao is a research scientist in the Distributed Scalable Systems Division of the University of Southern California Information Sciences Institute. Currently, he is working on the JESPP project, which has the goal of supporting very large-scale distributed military simulation involving millions of entities. Within the JESPP project he is developing a suite of monitoring/logging/analysis tools to help users better understand the computational and

behavioral properties of large-scale simulations. He received his B.S. degree in EECS from UC Berkeley, and his M.S. and Ph.D degrees in Computer Science from Rutgers University.

Michael D. Anhalt is retired a Commander, USN, Surface Line with over 23 years of operational experience, including specialties in Amphibious Warfare, Surface, Undersea, and Strike Warfare, and tactical training. He has planned and directed system-engineering efforts in modeling & simulation and their integration with C2 systems. He supports planning and conducting war fighting exercises and experiments, prototype development, and new technologies for C2 Systems. He holds an M.S. degree in Educational Technology.

Jacqueline M. Curiel is a research psychologist at Alion Science and Technology and a co-founder of Behavioral Cognition and is a consultant to IdeaDaVinci. She received both her M.A. and PhD degrees in Psychology from the University of Notre Dame, where her research focused on spatial cognition and mental representations in narrative comprehension.

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Philip Colon
Toyon Research Corporation
Goleta, CA
philipc@toyon.com

John Tran, KeThia Yao
Informaton Sciences Institute
Marina del Rey, CA
{jtran, kyao}@isi.edu

Michael Anhalt, Jacqueline M. Curiel
Alion Science and Technology
Marina del Rey, El Cajon, CA
{manhalt, jcuriel}@alionscience.com

INTRODUCTION

This paper focuses on building a foundation for a research effort on modeling situation awareness (SA) in synthetic theater of war (STOW). We present a relevant research problem, and a description of how it can be modeled. We focus on SA because it has widespread relevancy throughout the military community and at all levels of the command hierarchy. We are also interested in SA because, as a complex mental state that is composed of numerous cognitive processes, it is a particularly challenging modeling problem. Being able to successfully model SA will have at least a two-pronged benefit, in our view. First, it would validate our assumptions of the results of Human-in-the Loop (HITL) exercises in which human participants are a part of the simulation. Second, our approach is applicable to SA-related issues, including command and control (C2) and training.

Motivation

There are two accepted experimental methods for evaluating sensors technology: HITL experimentation and Monte Carlo Constructive (MCC) experiments, which are statistic-based constructive experimentation of sensor models. For HITL experiments, SA output is a function of human behavior. The use of constructive runs, up to this point, in sensor modeling and simulation experiments has been conducted independently of consideration for human interactions and attempts to model situation awareness have been limited to its more perceptual aspects. HITL experiments yield a wealth of data and if the MCC methodology can be used to develop tools to give analysts a synthesized encapsulation of events akin to the information provided by the HITL players, they can make better use of resources (time and personnel) to make better decisions.

Our approach is directly tied to ongoing HITL experimentation by the Forces and Modeling Simulation (FMS) Group in the J9 Directorate at the US Joint Forces Command (JFCOM), the evolving sensor modeling technology by Toyon Research Corporation, and the research and support in synthetic battlespace by Alion Science and Technology.

General Overview

Our proposed SA analysis framework, in the context of STOW, specifically in Joint Semi-Automated Forces (JSAF) simulation software, can be summarized as follows. The experiment consists of a game that is played among two or more potentially adversarial forces (i.e., blue, red, and green cells). The objective of the red and blue cells is to tactically outmaneuver the adversary. These experiments operate on the assumption that complete and superior SA, relying on the aid of sensor technology, is the key to success. In these experiments, players demonstrate SA when they detect and accurately interpret sensor data.

For our purposes, Figure 1 illustrates the flow of information from sensor data (input to player) to SA interpretations (output from player): sensor data and other simulation information are fed into a proverbial cognitive black box, resulting in SA. In the case of the HITL experiments, the black box represents the human players' cognitive processes involved in updating their mental model of the situation based on information from sensor data, prior knowledge, and their previous SA. The outputs of these processes are the SA products. In the case of constructive simulations, as there are no human interactions, the formulation of these processes is algorithmic.

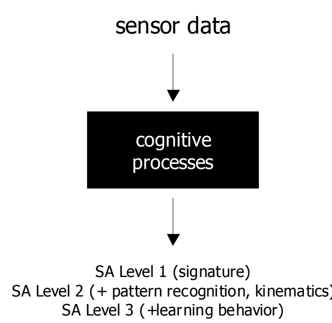

Figure 1. Information Flow from Sensor to SA

PROBLEM DESCRIPTION

The research problem considered here focuses on developing a situation template of emplacement to be used for future MCC experimentation. We first define situation awareness and its use in HITL experimentation. We then describe the sensor simulation platform and software and the possible way in which the algorithms are implemented. Finally, we will consider a case study of SA using data collected from human players.

Situation Awareness Defined

There tends to be widespread agreement as to when good and poor SA is observed, but the numerous definitions of SA illustrate the difficulty of precisely defining SA. Many of these definitions are not useful for our purposes because they do not provide a sufficient framework for specifying the variables that are likely to influence SA. Perhaps the most widely accepted view is that of Endsley's (1998) multi-level approach. This view has come to be adopted by the military community for research, training, operations, and other purposes, and provides a framework suitable for our purposes.

According to Endsley, SA can be described as consisting of perception, comprehension, and projection (see Figure 2). These levels represent the products of separate cognitive processes, yet the products from one level are influenced by those of other levels.

The perceptual level involves the detection, recognition, and identification of elements that define a specific situation. Perceptual SA relies on available sensory information, (e.g., from sensors in the case of a player in a HITL experiment) and the player's prior knowledge (e.g., object patterns/schemas activated in memory) to identify individual situation elements and object groups and their characteristics. Level 1A perception corresponds to the identification of individual entities (e.g., a tank); Level 1B perception corresponds to the identification of a grouping of entities (e.g., a mechanized brigade). The sensor fusion processes that are involved in associating tracks from different sensor sources or in grouping entities reflect perception.

The comprehension level (Level 2) reflects an understanding of the current situation, mapping perception to function. In battlespace, comprehension involves identifying the enemy's current activities.

Finally, the projection level (Level 3) reflects predictions about the trajectory of the situation based on the products of the lower levels of SA and prior knowledge. In battlespace, projection corresponds to intent: what will the enemy do? Our contribution to this paper focuses on how MCC experimentation can accomplish the mapping of perception to function thus involving both Level 1 and 2 SA.

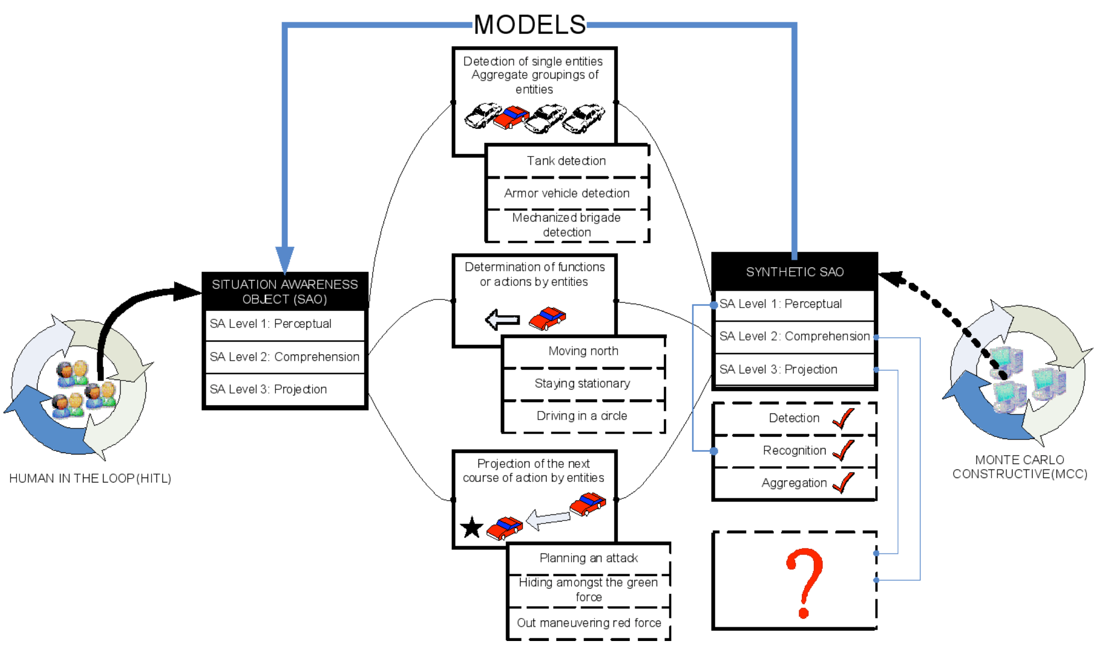

Figure 2. Endsley's (1998) Multi-Level Approach to Situation Awareness

HITL Experiments

USJFCOM conducts Joint Urban Operation (JUO) series of exercises in synthetic domains using human-directed computer simulation tools, such as JSAF, to explore and analyze current and future Joint war-fighting capabilities. HITL actions and interactions are important components of these experiments, where humans control the activity and influence the outcome of the exercises. Humans control simulated Intelligence, Surveillance, and Reconnaissance (ISR) sensors and use Situation Awareness Objects (SAOs) to declare and share their perceptions regarding model generated detections and track objects.

Situation Awareness Objects (SAOs) in HITL

In order to evaluate the effectiveness of game-play in the JUO exercises, we employ a novel tool called SAO, which is a method of recording information about red force entities that has only been used this series of experiments (Anhalt, 2006). The SAO is a compact package of information that players create and place on a shared terrain map that contains their thoughts, assumptions, and understanding about the enemy. Figure 3 is an example input screen in JSAF that allows puckers to annotate their SA state (create an SAO) during game play. SAOs are created by having players input information about the state of the entities.

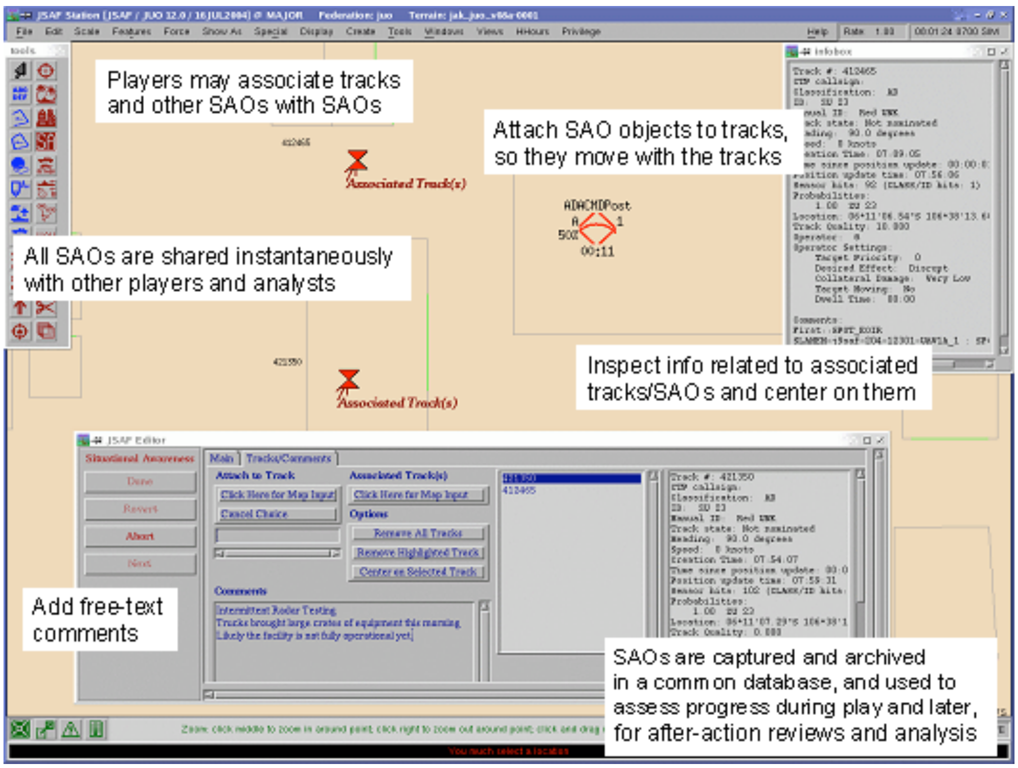

Figure 3. An Example Input Screen in JSAF

Collect Data from JUO/HITL Experiments

The data to be used for the model comes from JUO/HITL experiments, including electronic data that are captured and archived during each trial (e.g., ground-truth unit information of all enemy, friendly and neutral entities, enemy unit track locations as perceived by the sensors and players) and SOA information. SAOs are command and control tools designed for players to assess sensor results and share their findings. SAOs are key to evaluating the player's understanding of the battlespace and include player comments.

SENSOR MODELING: URBAN RESOLVE 2015

The vast developments in the fields of computer engineering and computer science have allowed for the efficient modeling of increasingly complex and computationally expensive sensor systems. As technical advances are made, additional resources become available for many problems that may have strained computing resources in the past, if they were possible at all. One highly effective use of modeling and simulation is the rapid prototyping of future systems. This use has allowed researchers to implement and discover new ideas based on state-of-the-art technological advances, as well as adapting to changing environments and current day military defense and defeat needs.

For the last several years, JFCOM HITL experiments have focused on asymmetric threats and have explored advanced future sensor technologies as solutions to defeat these threats. In so doing, a paradigm shift has occurred whereby HITL player involvement was expanded to involve interpreting formerly incidental pieces of information, or otherwise insignificant simulation artifacts, and recognizing that those events play a formal part of understanding the enemy. For example, in Millennium Challenge 02 and Urban Resolve Phase 1 in 2004, only the graphical representation of an entity was relevant; events such as digging and loitering within a group were not significant or were simply not a capability that existed in the simulation. As implemented in the J9 Directorate's Urban Resolve 2015 (UR2015) experiment of 2006, interpreting these events was critical to understanding SA. HITL players were trained to expand the scope of SAO involvement as the primary means of capturing the new pieces of information. SAOs became the central component to threat identification and interdiction within the experiment.

Description of SSAO

This paradigm shift also had the affect of creating a larger separation between HITL and MCC results by enhancing the overall impact human interpretation of events had on the experiment outcome. With MCC based experimentation focused on Level 1 SA, our contribution in this paper will make an evaluation of official UR2015 trial run SAO data, and use that data as a means to facilitate generating higher-level SA in MCC runs.

Our ultimate intent is to successfully bring together the most beneficial elements of HITL experiments, namely the unique perception abilities brought by players, and the scalability and efficiency of an MCC experiment. To effectively model patterns of player performance, the concept was developed to automatically generate SSAOs for MCC experiments. The SSAO is a generic construct that will facilitate capturing all three levels of SA in an MCC experiment in a manner parallel to the SAO in a HITL experiment. These objects encapsulate and automate the (1) detection of entities and the grouping of these detections, (2) identification of the activities of these entities, and (3) derivation of heuristic models for intent of the opposing force as represented by the entities. Figure 4 below demonstrates the three levels of SA that would be required to be encapsulated by an SAO/SSAO during HITL and MCC Experimentation.

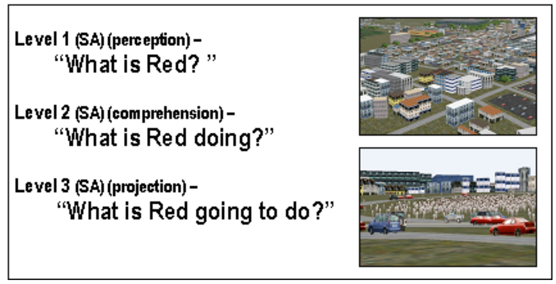

Figure 4. Three Levels of SA to be Captured by SAO/SSAO

SLAMEM: The MCC Simulation Testbed

JFCOM sponsored large scale HITL experimentation, including UR2015, has used the Simulation of the Location and Attack of Mobile Enemy Missiles (SLAMEM™) for simulating ISR capabilities in the JSAF federation. SLAMEM is an entity level, event based simulation that was developed for analyzing the performance of coordinated command, control, communications, intelligence, surveillance, reconnaissance (C4ISR) and targeting systems against time-critical mobile targets. SLAMEM has also been utilized in performing numerous MCC experiments on behalf of JFCOM. SLAMEM's role in supporting surveillance and targeting activities includes analyzing advanced C4ISR architectures. SLAMEM analyses have several objectives, including: (1) quantifying the potential improvements in effectiveness provided by the advanced architecture; (2) deriving the performance required from the technologies to achieve specific mission-level goals; and (3) developing new CONOPS for using the technologies most effectively. As the threat environment evolves, it has become more important to consider human perception factors when making the above 3 assessments.

MCC Experiments

Monte Carlo based simulations are closed form constructive processes that have no human interaction during runtime. The results of MCC experiments are dependent on the scenario metrics and random statistical variations from run to run, and are initiated with a unique random seed. These statistical variations can hinder meaningful results from MCC experiments if care is not taken to make sure a sufficient number of trial runs are completed (that is, random variations alone should not dictate the outcome of any run). This, however, is generally not a road block even when the number of trial runs is large. This is due to the fact that MCC runs do not require constant monitoring and lend themselves rather well to batch processing for this reason. The lack of the human component allows for greater scalability in the number of variables experiments can explore.

A limitation of MCC runs is that only the most basic levels of perception are considered for evaluation. Specifically, for SA Level 1, the acquisition of entities in the environment, and ability to maintain persistent surveillance has been the main focus. This is primarily due to the fact that there are no human interactions, and thus no human providing insight into the problem. But for MCC experiments to maintain their relevance, they must adapt to the growing trends of enhanced perception requirements.

Modeling SA in MCC with SSAO

The HITL experiments place an emphasis on the importance of human interactions and the output of the experimentation is a function of human behavior, and is measured using the metrics of Situation Awareness (Curiel, Tran, Anhalt & Yao., 2005). On the other hand, up to this point, sensors modeling and simulation experiments in the context of constructive simulations, by definition, have been conducted independently of consideration for human interactions. Notably missing is the lack of focus on a situation model.

Currently, MCC experimentation is developed with underlying fusion algorithms that can provide a means of synthesizing rudimentary components of SA. These components make up the first level of SA which answers the so-called "what" question. In the case of the models that have been experimented, the "what" question answers the specific questions of what is being observed or detected by the sensor models. They also provide, with the use of various heuristic algorithms, the ability to aggregate the detections into composite units, also referred to as Level 1B SA (Tran, Yao & Curiel, 2004). For example, the detection of a group of "metal" vehicles by the sensors can be funneled through the Fusion Center and the output is classified as a mechanized brigade (Castleberg, Colon & Berger, 2006). The ability to extend the constructive experiment model to cover the second and third level of SA in MCC experiments would provide a more complete experimental framework that validates the effectiveness of sensor models – and doing so from a statistically relevant analysis standpoint.

Automated Level 1 SA in UR2015

The UR2015 HITL experiment explored a trade space containing a wide array of sensor technologies. Each sensor, depending on its underlying phenomenology as well as its quality, aided situation awareness to varying degrees. This variability was characterized by confusion matrices. Confusion matrices were defined to be unique for each sensor, and also to provide a perceived view of the entities within the environment based on 3 dimensions (quality, camouflage, and azimuth angle). Confusion matrices represent the exploitation processes, whether automated or human-aided, which transform sensor data into detection and classification outcomes. Equation 1-1 (equation parameters are defined in Castleberg et al., 2006), commonly known as Johnson's criteria (Johnson, 1958; O'Connor, 2003), was used to determine the probability of detection, correct classification and identification of entities in the environment.

$$P \cong \frac{\left(N/N_{50}\right)^{\left(a+bN/N_{50}\right)}}{1+\left(N/N_{50}\right)^{\left(a+bN/N_{50}\right)}}$$

(1-1)

The outcomes of using Johnson's criteria per entity were used to populate the values of the confusion matrices. Figure 5 illustrates a generic example of a confusion matrix.

SA is initiated through sensor tasking and is developed through outcomes of sensor-target interactions and subsequent confusion matrix draws. That is, if say 10 entities fall into a single beam of a sensor, each of those 10 entities would be perceived separately and generate 10 distinct sensor-target interactions.

Perception

Ground Truth

		IDENTIFY						RECOGNIZE			
TRUTH	Pd	M35	SEDAN	T_TRAILER	T_72B	T_90	ZIL_131	CAR	TRUCK	TANK	UNKNOWN
M35	0.7	0		0.001	0.01	0.01	0.001		0.03	0.01	0.94
SEDAN	0.4		0.001					0.01			0.99
T_TRAILER	0.9	0		0.006			0.002		0.05		0.94
T_72B	0.7	0.03			0	0.003				0.027	0.94
T_90	0.7	0.03			0	0.003				0.027	0.94
ZIL_131	0.6	0		0.001			0.003		0.02		0.97
FALSE	1	0.02	0.022	0.022	0.02	0.022	0.022	0.02	0.02	0.022	0.8

Figure 5. Example of the Format for a Confusion Matrix

An important development in the field of modeling and simulation has been the change in focus from a strictly entity based visual perception of the enemy, to a more context-based perception of who is likely to be an enemy (Ceranowicz, Torpey, & Hines, 2006). This change in methodology has had a vast impact on the M&S sensor development community, and indeed on the players who control the sensors and interpret their output. The determination of who is likely to be an enemy is no longer based on what the entity looks like, but by viewing types of evidence such as the behavior of the entity at any given time, the accessories carried by the entity, and any actions the entity happens to be engaged in. The challenge of modeling and simulation is to make sure that each piece of evidence is sufficiently well modeled so that a HITL player has a chance to recognize the evidence, and discriminate with enough confidence targets of interest amongst the larger general population.

The scope of UR2015 was defined to provide a solution of persistent surveillance unmanned aerial vehicles (UAVs) fitted with high resolution imagery and video capable of detecting on the highest zoom setting enough of the pieces of evidence to address the problem scope. UR2015, with all the advanced sensors available to the players, was still only automated to the players SA Level 1 perception. Using Johnson's Criteria and assigning each piece of evidence a mean critical dimension, Equation 1-1 can be used to generate the probability of detection, correct classification, and identification for accessories and rudimentary actions, such as kneeling or loitering. When time is considered (i.e., an analyst reviewing sensor data over time), we may achieve recognition of behavior by utilizing the zoom feature of the video. It has been determined that to correctly classify small pieces of evidence, an image with resolution of better than 1cm is required (Castleberg et el., 2006). The UR2015 sensor solution required multiple looks in order to build sufficient confidence in a particularly small piece of evidence. The information provided over multiple looks was updated using Bayes' rule, Equation 1-2,

$$P^{n+1}(i \mid E^{n+1}) = \frac{P^{n}(i) \cdot P(E^{n+1} \mid i)}{\sum_{k=1}^{N} P^{n}(k) \cdot P(E^{n+1} \mid k)} \quad \text{for each } i = 1, N \tag{1-2}$$

and only when the belief in the truth identity of the evidence was reached (for UR2015 this threshold value was typically set to 0.80) a track was generated, containing information about the host entity's location and velocity, as well as a list of recognized pieces of evidence. Players then were left with the assignment of determining if any given piece of evidence, or the evidence as a whole, constituted suspicious activity. These tracks, in addition to the steaming video, provided the players with the necessary information to recognize suspicious behavior and create SAOs to reflect their SA during game play. Table 1 shows a listing of available SAO types, as well as their relative frequency or appearance during game play.

Table 1. UR2015 SAO Types and Frequencies

SAO Types	Frequency
TerrorAct Other	42
Terror Act Meeting	8.5
TerrorAct Surveillance	1
TerrorAct Suspicious	4
TerrorAct Loitering	34
TerrorAct Fleeing	2
TerrorAct Event	8.5

SAO CASE STUDY

Of critical importance to today's military is the threat of the improvised explosive devise (IED). For our consideration, we used data from actual events from UR2015 constituting an IED emplacement. The dataset was mined for TerrorAct SAOs where the players concluded that an IED placement was in progress or imminent based on one of several pieces of evidence. We define an IED emplacement scenario to be composed of the following: ingress of a vehicle to a location along the side of a sparsely populated road, 2-man team emerges and loiters, 1 of the 2 proceeds to the center of the road and kneels with a shovel, an IED is left behind, individuals proceed to the car and mount for egress. The process in sum lasts for no more than 30 minutes. The scenario also contains persistent high resolution imagery surveillance with one Predator viewing the area. Figure 6, a screen capture taken from the actual simulation tool used by players during UR2015, illustrates the scenario graphically.

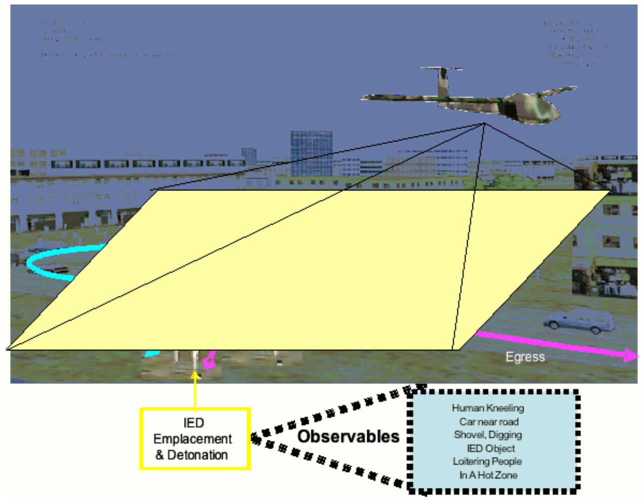

Figure 6. UR2015 IED Emplacement Scenario

SAO Case Study Results

The IED emplacement scenario was an important element of the UR2015 HITL trial runs, and players were trained on the indicators, or pieces of evidence, to look for to properly assess that situation. Figure 7 shows the pieces of evidence that composed each event and the relative frequency that each appeared as part of the players' decision-making process. For example, according to Figure 7, a player indicated that a "hot spot" was a relevant piece of evidence in 90% of SAO TerrorAct declarations.

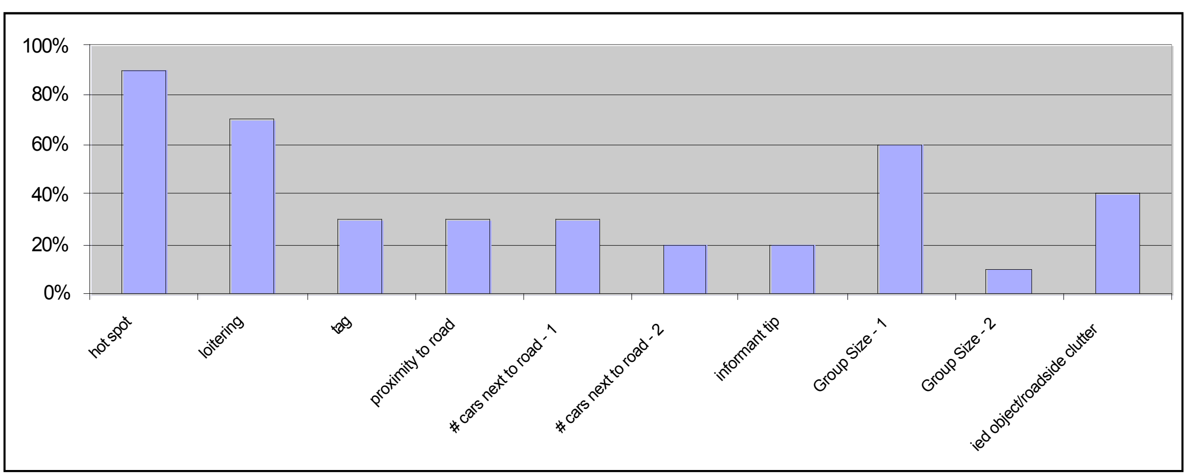

Figure 7. UR2015 Evidence and Frequency for Determining IED Emplacement TerrorAct SAOs

The UR2015 experiment scenarios were defined to bring together many aspects of behavior and actions. For players to identify a threat, they would have to identify several pieces of evidence and correlate them with each other. Figures 8 and 9 show the various pieces of evidence that players associated with IED emplacement events. Figure 8 shows that, on average, each IED emplacement SAO contained 4 distinct pieces of evidence.

Figure 9 shows that that the 10 IED emplacement SAOs from UR2015 were composed of 10 distinct pieces of evidence in different proportions. This data shows that, for example, most IED activity happened within a predefined "hot spot", in the presence of a single car parked next to a road, with a lone individual in the near vicinity.

The data showed that at no time was a single piece of evidence sufficient to declare an IED Emplacement. In fact, on average, when a player designated an SAO, there were 4 pieces of evidence that contributed to it.

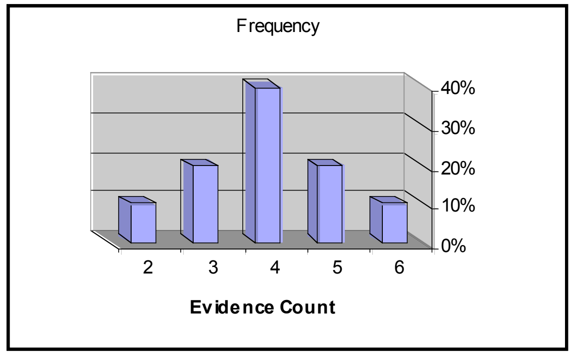

Figure 8. SAO Evidence Counts

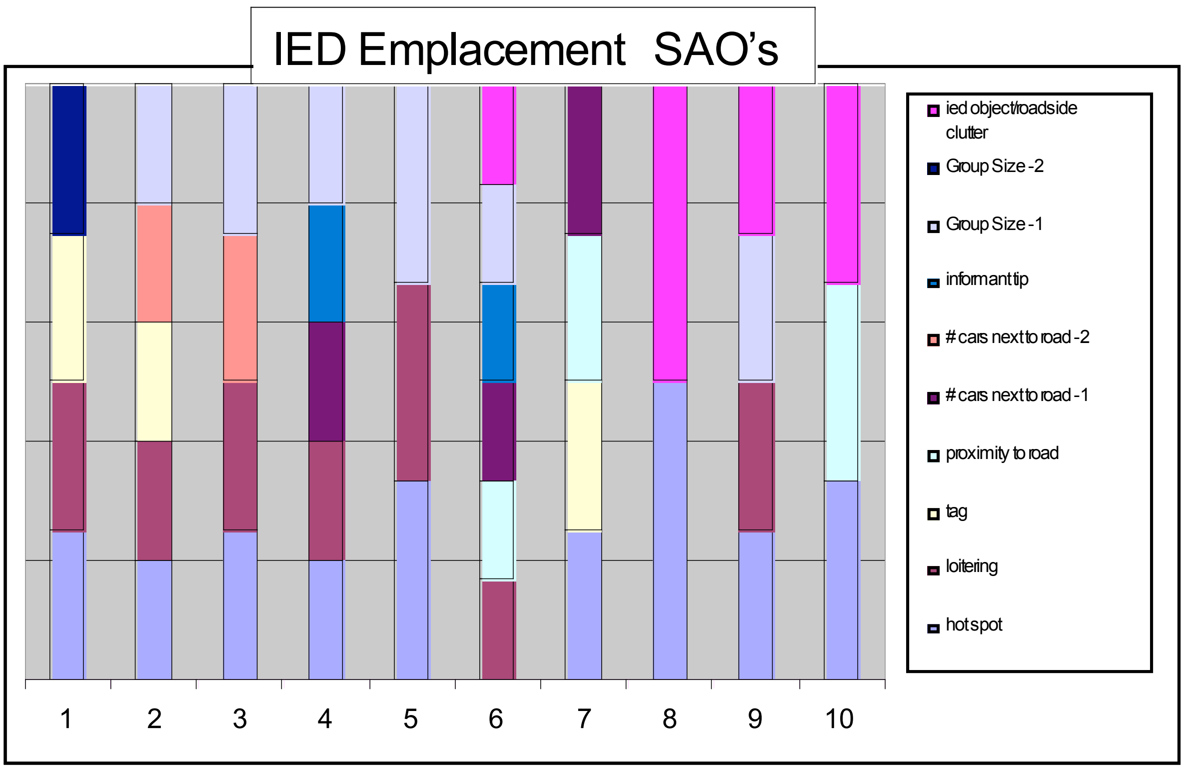

Figure 9. Evidence proportions for 10 IED emplacement SAOs

From SAO to SSAO

As mentioned previously, MCC runs are able to use algorithms focused on kinematics and features to determine rudimentary levels of SA. But these algorithms are not sophisticated enough to evaluate distinct measurements and group them together based on known, or learned, patterns to assess higher levels of SA. By using SAO data, we can train the algorithms to watch for specific pieces of evidence, each depending on the mission or CONOPS. Specifically for our test case of an IED emplacement, we may populate Table 2 from the SAO player data.

Table 2. Table of Evidence of IED Emplacement, with Definitions

Categories	Type	Specific	Definition
Actions	Loitering	Loitering	Individual standing or kneeling in roughly same location for several minutes
	Proximity To Road	Proximity To Road	Any action, location, or information located at roadside
Counts	Group Size	Group Size = 1	Observed individual is acting alone
		Group Size = 2	2 observed individuals close to one another
	Vehicle count parked at roadside	Vehicle Count = 1	Observed one vehicle parked along roadside
		Vehicle Count = 2	2 observed vehicles parked along roadside
Objects	Tag	Tag	A person or vehicle with any type of tag
	Object on Road	IED/Clutter object	An observed object laying on the road (either a roadside clutter or IED)
Information	Location	Hot Spot	Action or object observed in known area of interest
	Tip	Informant Tip	White cell injection that suspicious activity is taking place.

IED emplacements in the real world vary in every dimension, so we focus on the essential elements of an emplacement to keep the scenario tractable for analysis. A review of the SAO data suggests an a priori emplacement template for generating SSAOs in MCC runs, indicated by Figure 9.

RESULTS AND DISCUSSION

The research reported here is still in early developmental stages. However, we feel that that the direction we are taking offers vast potential for improvement of human performance in SA. One such example is the interplay between sensor development and human performance whereby behavior drives the technological requirements that contribute to sensor development. For example, looking at the evidence a player relies on is informative about the sensor technologies that are valuable. Being able to determine the physical attributes of the entities, as seen through stealth view, that were important to players discovering suspicious activity would lead us to conclude a need for high resolution cameras capable of detecting such attributes. When factoring in the need to have these cameras mounted on a UAV, aerostat, or towers operating at low light levels and at night etc. then player outcomes help define technology requirements.

Other potential applications to our approach include the following:

- Further refining SAOs to allow for automation between sensor and player output.
- Training for SA, such as by identification player biases.

CONCLUDING REMARKS

Human-In-The-Loop (HITL) experimentation provides researchers with firsthand data of how sensors and sensor systems are utilized by the players. Through observation during trial executions, researchers and analysts can watch the players while they make important time critical decisions on how to improve their situational awareness through the use of one or more sensors in theater. SAO objects are the key data element for understanding the players' choices at any given point in time. Analyses of these data can yield important information about how the sensors or sensor systems were employed, and what situations/scenarios were the most useful. Understanding this data better can illustrate operational needs more clearly, which can thus affect the design process of the sensors or systems. As for systems currently fielded, these data can provide insights on how to tune the sensors for better effectiveness during varying conditions.

Even with the benefits of human interactions and decision-making during sensor effectiveness studies, due to the fact that HITL experimentation requires a great deal of on-site personal support and financials resources, Monte Carlo constructive simulations are an attractive alternative. MCC runs require much less support than HITL experiments and are quite reliable at highlighting the capabilities of many sensors and sensor systems over a wide range of conditions. Currently, the lacking elements of Monte Carlo constructive simulation runs involve higher levels of situation awareness, such as the process of understanding incoming sensor data, associating tracks based on this data, and deducing enemy intent. By developing an algorithmic approximation to determining SAOs based on previous HITL data points, Monte Carlo constructive simulation runs can achieve a higher level of situational awareness that is not currently being obtained. Encapsulated within SAOs are keys to understanding the above mentioned process where a player takes sensor data and uses it to update the overall knowledge of the battle space. The outcome of the constructive runs can therefore expand upon the notion of sensor and sensor system capabilities to include new areas such as the usability of the sensors and sensor systems.

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REFERENCES

Anhalt, M. (2006). Situational Awareness Objects (SAOs), A Collaborative Toolset for Players, Controllers and Analysts. *Interservice/Industry Training, Simulation, and Education Conference Proceedings*, 492-499.

Castleberg, P. A., Colon, P. E., and Berger, J. A. (2006). Modeling and Simulation of Sensor Systems to Experiment Against Contemporary Asymmetric Urban Threats. *Interservice/Industry Training, Simulation and Education Conference Proceedings*, 596-604.

Ceranowicz, A., Torpey, M. and Hines, J. (2006). Sides, Force, and ROE for Asymmetric Environments. *Interservice/Industry Training, Simulation and Education Conference Proceedings*. 384-391.

Curiel, J.M., J.J. Tran, M. D. Anhalt, and K-T. Yao. (2005). Developing Situation Awareness Metrics in a Synthetic Battlespace Environment. *Interservice/Industry Training, Simulation, and Education Conference Proceedings* . Orlando, 1451-1459

Crago, S.P., McMahon, J. O., Archer, C., Asanovic, K., Chaung, R., Goolsbey, K., Hall, M., Kozyrakis, C, Olukotun, K., O'Reilly, U., Pancoast, R., Prasanna, V., Rabbah, R, Ward, S, & Yeung, D. (2006). CEARCH: Cognition Enabled Architecture. *Proceedings of the Tenth Annual High Performance Embedded Computing Workshop*.

Endsley, M. (1995). Toward a theory of situation awareness. *Human Factors, 37*, 32-64.

Endsley, Mica R. (1998). Theoretical Underpinnings of Situation Awareness: A Critical Review in Micah R. Endsley and Daniel J. Garland (Eds). *Situation Analysis and Measurement*. pp 3-32. Mahwah, N.J.: Lawrence Erlbaum Associates, Publishers.

Endsley, M. R. & Garland, D. J. (Eds.) (2000). *Situation Awareness: Analysis and Measurement*. Mahwah, NJ: Lawrence Erlbaum Associates.

Johnson, J. (1958). Analysis of Image Forming Systems. *Proceedings of the Image Intensifier Symposium*, 249-273. Warfare Electrical Engineering Dept., US Army Engineering

Research and Development Laboratories, Ft. Belvoir,

JOINT FORCES COMMAND. MC02 Experiment: http://www.jfcom.mil/about/experiments/mc02.htm

O'Connor, J., Driggers, R., Vollmerhausen, R., Devitt, N. & Olson, J. (2003). Fifty percent Probability of Identification (N50) Comparison for Targets in the Visible and Infrared Spectra. *SPIE Optical Engineering, 42*, 3047-3052.

Tran, J.J. K-T. Yao, and J.M. Curiel. (2004). An Interdisciplinary Approach to the Study of Battlefield Simulation Systems. *Interservice/Industry Training, Simulation, and Education Conference Proceedings*, Paper # 1866 pp. 1-9.