Modeling Situation Awareness for Army Infantry Platoon Leaders Using Fuzzy Cognitive Mapping Techniques

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ABSTRACT: *This paper describes work on the development of an actionable model of situation awareness for Army infantry platoon leaders using fuzzy cognitive mapping techniques. Developing this model based on the formal representation of the platoon leader provided by the Goal-Directed Task Analysis (GDTA) methodology advances current cognitive models because it provides valuable insight on how to effectively support human cognition within the decision-making process. We describe the modeling design approach and discuss validating the model using the VBS2 simulation environment.*

1. Introduction

This paper describes our novel approach to providing an actionable model of SA using fuzzy cognitive maps (FCM) that encompasses all three levels of situation awareness (SA) (i.e., perception, comprehension, and projection). Our cognitive model, the SA-FCM model, is built directly from the goals, decisions, and essential information requirements associated with effective decision-making in a domain. As such, the SA-FCM represents a computational naturalistic decision-making model.

Traditional approaches in cognitive modeling relied upon presumptive and assumptive principles derived from basic rational behavior. For example, cognitive architectures, such as ACT-R (Anderson and Lebiere, 1998), SOAR (Newell, 1990), COGNET (Zachary & Le Mentic, 1999), and CoJACK (Evertsz, Pedrotti, Busetta, Acar, & Ritter 2009) provide structural properties of a modeled system that instantiates cognitive models developed from rule-based logic, decision trees, or production and planning rules.

Alternatively, Task Network modeling tools, such as Micro Saint and C3TRACE provide a framework for representing human behavior as a decomposition of operator tasks (Warwick, Archer, Hamilton, Matessa, Santamaria, Chong, Allender, & Kelley, 2008). Finally, intelligent agent-based systems, such as the Beliefs, Desires, and Intentions (BDI; Bratman, 1987) framework and R-CAST (Fan, Sun, & Yen, 2005) require a priori knowledge and prior experience.

While these cognitive models have advanced the artificial intelligence community, a notable shortcoming of these approaches is that the decisions represented by these models are primarily driven from inferences, behaviors, and rules that do not generally include situation awareness as a cognitive factor. Extensive research has identified SA as a major factor behind the quality of the decision process (see Endsley & Jones, 1997; Klein, 1989; Kaempf, Wolf, & Miller, 1993; Cohen, 1993).

Accordingly, recent prior approaches to computationally modeling SA have been examined, such as dTank (Ritter, Kase, Bhandarkar, Lewis, & Cohen, 2007) and CoJACK (Evertsz, et. al, 2009). However, we have found that these efforts only model the perception construct of SA (i.e., Level 1 SA), and generally do not include the comprehension (Level 2 SA) and projection (Level 3 SA) levels of situation awareness. In order to effectively model decision-making that reflects real world conditions, these higher-level SA constructs should be considered.

Thus, our SA-FCM model is an advancement to cognitive modeling because it incorporates not only Level 1 SA, but higher-levels of SA that is required to make decisions in a complex world. This is critical in domains such as military command and control, where sufficient data is not always available for developing a cognitive model that provides a realistic representation of the behaviors of the people involved (e.g., friendly forces, insurgents, and civilians).

The next sections describe the design of the FCM model. The following section discusses using VBS2 to validate the model. The paper concludes with preliminary results and highlights the strengths and weaknesses of modeling SA using a FCM. The significance of this effort is that it provides a modeling approach that utilizes SA as the primary driving force for effective decision-making and overcomes some of the limitations of rules, learning algorithms, and behavior moderators that are essential for other cognitive modeling systems.

2. Designing the SA-FCM Model

Our current work focuses on improving the representation of situation awareness through the use of Fuzzy Cognitive Mapping techniques. Our objective is to develop a model that replicates human cognition as it relates to SA. The SA-FCM model is designed from the relationship between goals, decisions, and SA requirements as represented by a Goal-Directed Task Analysis (GDTA) hierarchy (see Endsley, Bolté, & Jones, 2003).

Based on the theoretical model of SA provided by Endsley (1995), the GDTA process has been used in many domains to detail SA requirements. As such, it forms an exemplary template for incorporating human cognition into an actionable model by describing in detail not only a user's information data needs (Level 1 SA), but also how that information needs to be combined to form the needed comprehension (Level 2 SA), and projection of future events (Level 3 SA) that are critical to situation awareness thus providing a critical link between data input and decision outputs.

2.1 Fuzzy Cognitive Mapping

Conceptually, a FCM can be thought of as a combination of fuzzy logic and concept mapping. Fuzzy logic is derived from fuzzy set theory dealing with reasoning that is approximate rather than precisely deduced from classical predicate logic. It provides the application side of fuzzy set theory dealing with well-conceived real world expert values for a complex problem (Klir, St. Clair, & Yuan, 1997). FCMs use predefined knowledge, or constructs of the causality of concepts (represented as nodes), to define a system. FCMs are especially applicable in soft knowledge domains through their use of (symbolic) knowledge processing.

In a sense, the FCM provides an adaptive structure that affords qualitative reasoning as assessed from the current levels or states of a complex system along with quantitative elements (i.e., causal algebra). At the heart of a FCM is a graphical structure with variable concepts connected via cause/effect relationships. The strength of the causal connection is represented by a numerical quantity defined on the interval [-1, +1], with -1 representing an inverse causality and +1 meaning direct causality (Kosko, 1987). Additionally, fractional values are used for the causal connection when combinations of multiple nodes lead to an effect (e.g., a many-to-one relationship).

FCMs provide an efficient soft computing tool that supports adaptive behavior in complex and dynamic worlds (Siraj, Bridges, & Vaughn, 2001; Stylios & Groumpos, 2000) as well as reasoning characteristics that make it a significant support aid for analysts and decision-makers. A main advantage of FCMs is their flexibility in system design, modeling, and control (Papageorgiou & Groumpos, 2004). Their benefit lies in their capability to represent dynamic systems that can evolve over time, supporting dynamic timeline structures. Unique to FCMs is their ability to incorporate attributes as qualitative states, rather than hard numerical characteristics. FCMs are thus useful for constructing models of dynamic feedback systems, reducing the semantic gap between a system and the model of the system, and predicting the future state (i.e., Level 3 SA, projection) of a system, based on knowing the present state (Level 1 SA, perception).

2.2 The SA-FCM Model

The diagram below (see Figure 2.1) illustrates a high-level overview of the SA-FCM model. The model utilizes both top-down (i.e., goal driven) and bottom-up (i.e., data-driven) approaches.

Specifically, the top-down approach begins at the *Goal node*, which influences what the operator perceives from the available data in the world (i.e., the *Level 1 SA node*). Similarly, the operator's goal also influences *the Level 2 SA node* through (1) how much is comprehended (quantity) and (2) which data items are comprehended (quality), thereby effecting the nature of the comprehensions (i.e., the "so what" of the data). Furthermore, the operator's goal also has the same influence on projections (i.e., the *Level 3 SA node*). Collectively, these three nodes represent the SA Requirements submap of the overall SA-FCM model (see Figure 2.1), the content of which is derived directly from the GDTA hierarchy.

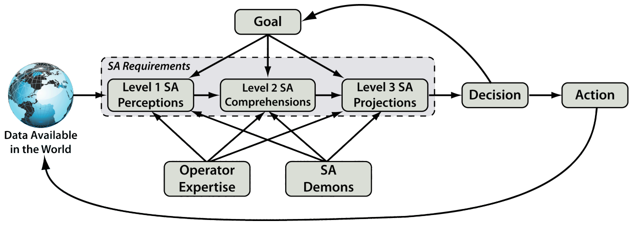

Figure 2.1: High-Level SA-FCM Model

The aggregate SA from these nodes affects the decision of the operator, which then influences the actions of the operator, and may influence the selection of the current goal of the operator. The *Operator's Expertise* and the presence of factors we have dubbed the *SA Demons* are nodes that can degrade or enhance the operator's SA in this process. For example, a novice operator may have trouble achieving the same level of high SA as an experienced operator given the same conditions (as they likely will not have the same models or schema for processing information). Additionally, the presence of certain SA Demons (such as data overload, requisite memory traps, misplaced salience, attentional narrowing, workload, fatigue and other stressors, complexity creep, errant mental models, or the out-of-the-loop syndrome) will limit the SA of the operator, (see Endsley, Bolté, & Jones, 2003 for more information on SA Demons).

Processing in this model can be either bottom-up or top-down, often in an alternating fashion. The bottom-up approach begins at the data node (i.e., *Data available in the world*). The available data determines the goal, which then influences each level of SA. Similar to the top-down approach, the operator's SA is affected by the *Operator's Expertise* and *SA Demons* nodes. The resulting decision is directed by the operator's SA, which then influences the current goal as well as actions taken. Moreover, each top-level node represents a submap that contains concepts and relationships that determine the output of its map. For brevity, only a brief description of the Goals submap, and the SA Requirements submap are provided.

2.3 FCM Algorithm

A fuzzy cognitive map is comprised of concepts and weights that can be categorized into three types of layers. First, the input layer contains the concepts that are directly connected to the external world. The middle layer of the FCM serves as a processing layer that integrates concepts from the input layers and directs them to the output layer. Complex FCMs (e.g., those with sub-FCM structures) can have multiple middle layers. The final layer is the output layer whose values are directed back into the external world, or back into the input layer if the FCM incorporates feedback explicitly. The FCM for this project is considered a complex FCM; the concepts on the middle layer are formed from multiple sub-map structures that contain additional middle layers that are directed to an output layer. Concepts that reside on the middle and output layers have activation functions that determine the output value of the concept. The activation function of a concept node (e.g., *Concept A*) is determined by (1) the value of each input concept that is directed into *Concept A*, and (2) the *influence* that each input concept has on *Concept A*. The activation function can be a global function (i.e., all concepts use the same function) or each concept can have a unique activation function. For example, a binary-state FCM will have a concept value of 1 if activated and a 0 if deactivated. Formally, the activation function is the summation of each input concept multiplied by its weight value minus a threshold value (see equation below). For a complete description of the mathematical process, see Kosko (1987).

$$A_x = (SA_{in} * w_{in}) - t_x$$

2.3 Goals Submap

The Goals submap defines the relationships of the main goal, its subgoals, and how each goal influences the other goals (i.e., the activation of one goal can cause the activation of other related goals). For example, the platoon leader GDTA hierarchy (see Figure 2.2) features seven goals under the main goal *attack, secure and hold terrain*. The overall FCM (Figure 2.3) details the causal relationships between these main goals, with each goal representing a node in the map. A total of 15 causal relationships (represented as arcs) with preliminary weight placeholders (e.g., w_{16}) were mapped between the nodes. For each of the seven goals, we created additional "sub-FCMs" using the subgoals as nodes and defined the causal relationships between sub-goal nodes.

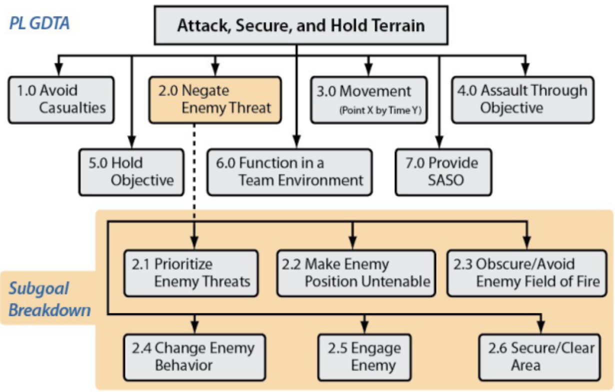

Figure 2.2: Platoon Leader GDTA, showing the main goal and subgoals

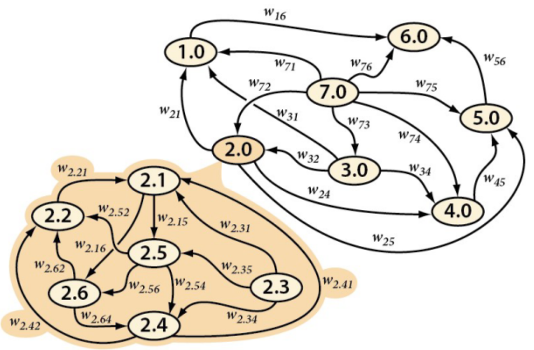

Figure 2.3: Overall FCM developed for platoon leader with sub-FCM representing sub-goal 2.0

2.4 SA Requirements Submap

The SA Requirements submap can be used to compute the amount of SA the operator has at each level for each SA requirement. The model accomplishes this by maintaining the hierarchical relationship of each SA requirement identified in the GDTA hierarchy and providing a SA score at each level. Consider the simple example submap shown in Figure 2.4. The nodes for this FCM would be obtained directly from the GDTA hierarchy. For example, the GDTA hierarchy identifies *Data Element A, B, and C* as Level 1 SA requirements tied to the Level 2 SA element *Comprehension ABC*.

The specific weights for this map are obtained from discussions with subject matter experts (SMEs). The SMEs are not asked to assign weight values, but rank the importance of each concept, from which the researcher develops the weighting scheme. For example, *Comprehension ABC can* occur if *Data Element A* is available and either *Data Element B* or *Data Element C* is available.

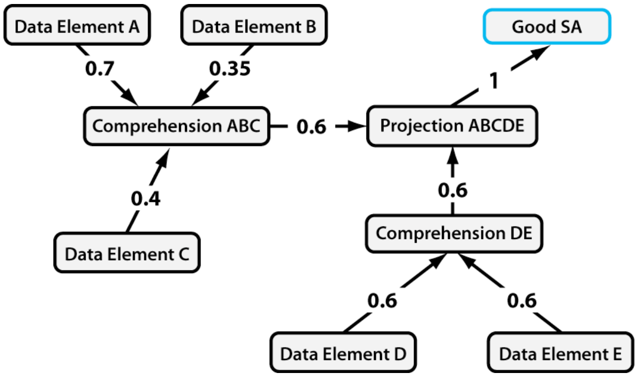

Figure 2.4: Conceptual SA Requirements submap of FCM translated from GDTA hierarchy (with sample weights)

From Figure 2.4, in order to have good SA, *Projection ABCDE* must be active. *Projection ABCDE* is only active if *Comprehension ABC* and *Comprehension DE* are both active. Since this is a simple sample case, it is easy to see that from the sample weight values, *Data Element A, D, and E* are the most the significant concepts. Thus, in this particular instance, it is impossible to have good SA without those data elements being presented to the user in a meaningful way.

3. SA-FCM Model in Practice

The SA requirements outlined in the GDTA encompass the militarily relevant aspects of the environment or background against which a military operation occurs known as Mission, Environment, Terrain and Weather, Troops, Time Available and Civil Considerations (METT-TC factors), the accurate depiction of which is necessary for good decision-making. The SA-FCM model incorporates those METT-TC factors and establishes relationships linking specific considerations to a decision as defined in the GDTA (see Figure 3.1).

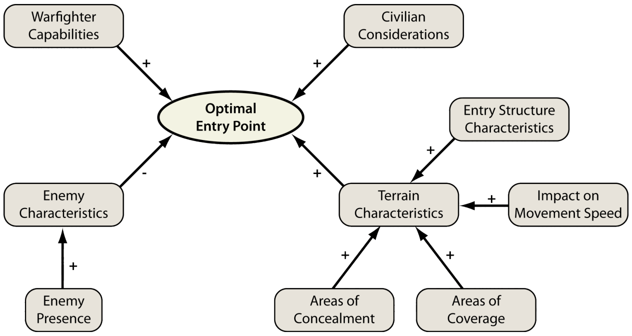

Figure 3.1: Abstracted version of the FCM of METT-TC factors influencing *Optimal Entry Point*

We provide an example to demonstrate how the weights were determined using the methodology defined by Kosko (1987). Our procedure parallels the methodology employed in the development of a FCM that modeled the behaviors of dolphins, fish, and sharks in an undersea virtual world (Dickerson & Kosko, 1994). For terrain considerations, specifically understanding areas of concealment, an Army Infantry Platoon Leader may want to know the following factors: humidity, type of road, and dew point. The infantry platoon leader interprets this information to understand if the road is traversable for covert and stealth operations. A lower dew point combined with a high humidity generally means that a dirt road would more than likely be wet, and therefore quieter, which is preferable for stealth operations. An example of how the SA-FCM represents this relationship is presented in Figure 3.2.

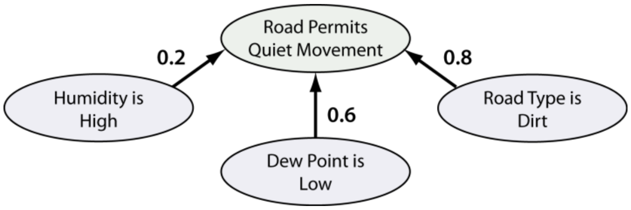

Figure 3.2: Example FCM detail showing METT-TC (terrain) factors

The weights are relative values, which are determined in conjunction with our SME, who prioritized the terrain-related factors. For this particular example, the critical factor to stealth movement is identifying the type of the road. Once it is established that a road is a dirt road, the platoon leader can then consider the dew point and humidity as factors, and the impact of those on stealth movement. As explained by the SME, even though the dew point and humidity are related, the platoon leader is more interested in the dew point, and only cares about the humidity in extreme situations. Thus, the condition for conducting stealth movements is primarily dependent upon the road type being dirt and the dew point being low. Consequently, the weight values for those factors are set such that if the nodes for *road type is dirt* and *dew point is low* are true, the *road permits quiet movement* node will be activated.

It is important to note that this process of prioritizing factors parallels the cognitive processes that humans naturally employ. It is easier to characterize an event by prioritizing the conditions that must be present for an event to occur. Conversely, the use of traditional modeling approaches, such as Bayesian Nets, requires quantifying events in terms of probabilities by associating an event to a set of conditions. For example, using a Bayesian approach, the SME would be required to provide the likelihood that the road permits quiet movement given the conditions that the humidity is high, the dew point is low, and the road type is dirt.

4. Validation

The SA-FCM model represents an actionable model of SA that is designed to mimic effective decision-making. The model is derived from a specific GDTA that establishes the goals, decisions, and SA requirements for a given role, in this case infantry platoon leaders. As such, the model considers the following information derived from the METT-TC factors: location(s) to position warfighters for engagement, area(s) for stealth movements, warfighter (i.e., Blue Forces), capabilities enemy capabilities, and Rules of Engagement (ROE) considerations (e.g., places to avoid due to civilian presence). The current output of the SA-FCM model will be a plan based upon those considerations. Thus, the SA-FCM model represents the SA for an infantry platoon leader whose plan is based upon information that has been gathered in the field. The effectiveness (i.e., success or failure) of the infantry platoon leader's plan will be primarily predicated on their SA level as represented in the SA-FCM model.

A VBS2 simulation was utilized to validate the SA-FCM model. Working with the SME, we narrowed the platoon leader GDTA down to one subgoal, *Determine Entry Point,* for the purpose of validation. Our Army SME identified this subgoal as one of the more critical for missions that are important to the Army. Additionally, this goal allowed us to quickly develop and implement the SA-FCM model for the validation exercise. The decisions and information requirements associated with this subgoal can be best represented by an infiltration operation that requires an understanding of the terrain and enemy locations and their capabilities in order to choose the correct entry location.

The simulation features a scenario where the warfighters' goal is to successfully enter a building. Depending upon troop size and capabilities, enemy size and capabilities, and the presence of civilians in public places, the model will need to determine where to strategically position Blue Force assets and avoid major civilian injuries. The scenario development was guided by a SME and is regarded as a representative of common modern Army operations involving clearing a building. The scenario is played in a default town that is available with the VBS2 simulation and it is populated with building architectures and non-playable characters (NPCs) that are common to a Middle Eastern setting.

Two SMEs with different areas of expertise were chosen to assist in the creation and validation of the SA-FCM. One SME, whose area of expertise is intelligence, focused on the information-gathering phase of the mission. Specifically, we discussed the intelligence that would be provided to infantry platoon leaders. The second SME has a background in maneuver and combat, and described how the intelligence would be used to devise a plan in accordance with the Army Combat Manual. Additionally, the second SME explained how specific METT-TC factors, such as areas of concealment and coverage, needed to be established prior to executing the mission. Each was interviewed at length with respect to their area of expertise. The resulting weights for the SA-FCM model and components for the VBS2 scenarios were developed independently of the SMEs.

A Turing test was completed to validate the model. The validation plan involved a SME serving as a confederate

(SME-A). SME-A was given information about a scenario outlined in the METT-TC factors. The same information was provided to the SA-FCM model. Both SME-A and the model produced a plan, which was translated into VBS2. The other SME (SME-B) reviewed the execution of each plan using the After Action Review (AAR) feature of VBS2. The AAR also provided performance measures that were collected for each run. Trial runs were conducted that varied the number of insurgents guarding the building. SME-B evaluated each plan by reviewing avenues of approach and avenues of departure, entry location to building, and how the Blue Forces were deployed. SME-B was unable to distinguish the plans devised by the SA-FCM from the plans devised from SME-A. These preliminary results suggest that the SA-FCM model was successful in developing plans that are consistent with Army procedure.

5. Discussion

The significance of the SA-FCM model is twofold. First, the model directly represents the SA requirements for army operations in terms of their relationship as METT-TC factors. Thus, the model is based upon the same information that a warfighter would need to make a decision. Secondly, the SA-FCM model represents decisions in real-time (or near real-time) by effectively comprehending and projecting a scenario based upon the METT-TC factors that is used by a human decision maker.

The following scenario provides an example of how the SA-FCM model can be used to support the warfighter. A platoon of Blue Force warfighters is traveling in a helicopter to a location close to an insurgent hotspot. The warfighters are commanded to clear a building occupied by the insurgents. The platoon leader is provided with a map and intelligence gathered about the area that includes information about the insurgents, terrain, and civilians (i.e., METT-TC factors). Ideally, an infantry platoon leader would prefer sufficient time to devise a plan that may include a detailed process of examining multiple courses of action (COAs). However, in this case, the platoon leader has to develop a plan before the helicopter lands. Thus, the platoon leader attempts to comprehend and make projections from data obtained from various sources, which can be a daunting challenge given the severe time constraints. The SA-FCM would be used to support the decision-making of the infantry platoon leader by mapping the relationship of the METT-TC factors, displaying the relevant considerations appropriately and recommending a plan. Consequently, an immediate area in which the SA-FCM model would prove beneficial is the planning phase of missions; the model could quickly develop and display a recommended plan that effectively supports the SA requirements for the infantry platoon leader.

5.1 Benefits of FCM Approach

An advantage to modeling SA with a FCM from the GDTA is that it allows for higher-level SA to be expressed explicitly. Neural networks, ACT-R, and intelligent agents generally can only model the relationship between input (i.e., perceived elements in the world) and output (i.e., decisions, behaviors, or actions). In these models, how Level 1 SA leads to a decision is unknown to the user as the computational processes are hidden in a “black box.” FCMs built on GDTA hierarchies, on the other hand, include Level 2 and Level 3 SA and are capable of modeling the relationship of how perceived elements (Level 1 SA) lead to comprehension (Level 2 SA), and how that leads to projection of future events (Level 3 SA) which are understandable to the user.

Thus, the SA-FCM will be tailored to fit and encompass the cognitive elements of the decision-making process. The SA-FCM model will incorporate warfighters’ decisions that are made when incomplete information is present (i.e., the platoon leader does not have enough information to make a decision) or when warfighters have information of questionable quality. In both cases, the model identifies the SA requirements that are essential to making the correct decision. Thus, we believe that this model provides a direct way of representing the user because it defines the user’s cognition using subjective terms rather than mathematical expressions. Consequently, the SA-FCM is a valuable approach for modeling goals, decisions, and SA requirements across the three SA levels and then translating that information into a complete actionable model.

5.2 Limitations of FCM Approach

A drawback with this methodology is that it solely relies upon the expert’s understanding of the work domain. This understanding can include not only the expert’s knowledge, but their ignorance, prejudice, or biases. Fortunately, FCMs can contain multiple experts’ perspectives by merging each expert’s FCM to create a new FCM that can represent the views of a number of experts in a unified manner.

Translating the GDTA to a FCM is also a challenge. It requires an elicitor that can form a very developed GDTA that contains unique goals and decisions. Since the translation is purely qualitative, the translation process also requires consistency amongst terms. For example, interchanging terms such as speed and velocity can become problematic because it may result in 2 separate

FCM nodes (i.e., one for each term), where they are the same concept.

5.3 Future Work

Future work for this effort will include the development and validation of a FCM for all of the remaining subgoals and goals described in the platoon leader GDTA hierarchy. The presence of multiple goals poses additional challenges because the model must also correctly represent the relationships between goals.

A related research direction we wish to pursue is how to represent and incorporate uncertainty within the SA-FCM model. An important feature of FCMs is their capability for addressing uncertainty. Thus, identifying and understanding the sources of uncertainty as it relates to SA is critical to resolving data with different degrees of uncertainty.

Additional future work also includes integrating the SA-FCM in an adaptive environment, so that the model can perform real-time decisions based upon real-time information. For example, the model will produce a plan and can modify it based upon real-time information that is gathered throughout the simulation. Currently, this type of real-time adaptable environment is not supported within VBS2.

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7. References

Anderson, J. R. & Lebiere, C. (1998). *The atomic components of thought.* Mahwah, NJ: Lawrence Erlbaum Associates.

Bratman, M. (1987). *Intentions, Plans, and Practical Reason.* Cambridge, MA: Harvard University Press.

Cohen, M. S. (1993). Metacognitive strategies in support of recognition. *In Proceedings of the Human Factors and Ergonomics Society 37th Annual Meeting*. Santa Monica, CA: Human Factors and Ergonomics Society.

Dickerson, J. A., & Kosko, B. (1994). Virtual Worlds as Fuzzy Cognitive Maps. *Presence, 3* (2), 173-189.

Endsley, M. R. (1995). Toward a theory of situation awareness in dynamic systems. *Human Factors, 37(1)*, 32-64.

Endsley, M. R., & Jones, W. M. (1997). *Situation awareness, information dominance, and information warfare* (Tech Report 97-01). Belmont, MA: Endsley Consulting.

Endsley, M. R., Bolté, B. & Jones, D. G. (2003). Designing for situation awareness: An approach to user-centered design. New York: Taylor & Francis

Evertsz, R., Pedrotti, M., Busetta, P., & Acar H. (2009). Populating VSBS2 with Realistic Virtual Actors. *Proceedings of the 18th conference on Behavior Representation in Modeling and Simulation*. Orlando, FL: U. of Central Florida.

Evertsz, R., Ritter, F. E., Busetta, P., Pedrotti, M., Bittner, J. L. (2008). CoJACK- Achieving Principled Behavior Variation in a Moderated cognitive Architecture. *Proceedings of the 17th conference on Behavior Representation in Modeling and Simulation*. Orlando, FL: U. of Central Florida.

Fan, X., Sun, S., and Yen, J. (2005). On Shared Situation Awareness for Supporting Human Decision-making Teams. *Proceedings of 2005 AAAI Spring Symposium on AI Technologies for Homeland Security*.

Kaempf, G. L., Wolf, S., & Miller, T. E. (1993). Decision making in the AEGIS combat information center. *In Proceedings of the Human Factors and Ergonomics Society 37th Annual Meeting*. Santa Monica, CA: Human Factors and Ergonomics Society.

Klein, G. A. (1989). *Recognition-primed decisions*. In W. B. Rouse (Eds.), Advances in man-machine systems research. Greenwich, Conn: JAI Press, Inc.

Klir, G., St. Clair, U. H., and Yuan, B. (1997). *Fuzzy Set Theory Foundations and Applications*.

Kosko, B. (1987). Adaptive inference in fuzzy knowledge networks. *Conference on Neural Networks,* 2, 261-286.

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

Papageorgiou, E. I. and Groumpos, P. P. (2004). Two-state learning algorithm for fuzzy cognitive maps. *Proceedings of the IEEE International Conference on Intelligent Systems*.

Ritter, F. E., Kase, S. E., Bhandarkar, D., Lewis, B. & Cohen, M. A. (2007). dTankUpdated: Exploring Moderated Behavior in a Light-weight synthetic Environment. *Proceedings of the 16th Conference on Behavior Representation in Modeling and Simulation (BRIMS)*. Orlando, FL: U. of Central Florida.

Siraj, A., Bridges, S. M., and Vaughn, R. B. (2001). Fuzzy cognitive maps for decision support in an intelligent intrusion detection system. *North American Fuzzy Information Processing Society*.

Stylios, C. D. and Groumpos, P. P. (2000). Fuzzy cognitive maps: A soft computing technique for intelligent control. *Proceedings of the 2000 IEEE International Symposium on Intelligent Control*, 97-102.

Warwick, W., Archer, R., Hamiliton, A., Matessa, M., Santamaria, A., Chong, R.S., Allender, L. & Kelley, T. (2008). Integrating Architectures: Dovetailing Task Network and Cognitive Models. *Proceedings of the 17th Conference on Behavior Representation in Modeling and Simulation (BRIMS)*. Orlando, FL: U. of Central Florida.

Zachary, W., & Le Mentec, J.-C. (1999). A framework for developing intelligent agents based on human information processing architecture. *Proceedings from IASTED International Conference ASC.*

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