Knowledge Visualization to Enhance Human-Agent Situation Awareness Within a Computational Recognition-Primed Decision System

Timothy Hanratty
US Army Research Laboratory
hanratty@arl.army.mil

Robert J. Hammell II
Towson University
rhammell@towson.edu

John Yen, Michael McNeese, Sooyoung Oh, Hyun-Woo Kim & Dev Minotra
Pennsylvania State University
{jyen, mmcneese, soh, hxk263, dxm401}@ist.psu.edu

Laura Strater, Haydee Cuevas & Dan Colombo,
SA Technologies, Inc.
laura@satechnologies.com
haydee.cuevas@satechnologies.com
dan.colombo@statechnologies.com

ABSTRACT

Recent operations in Iraq and Afghanistan have confirmed that in order to achieve effective Network-Centric Operations (NCO), innovative enhancement to military decision-making is desired. Required are processes and computational models that support the decision-makers' experience while promoting high levels of shared situation awareness (SA) – not only in the context of the external operating environment, but internally aligning the decision makers' mental model with the intelligent software agents working on their behalf. Towards this end, the aim of this research is to enhance the decision-maker's perception, comprehension, and projection of the underlying knowledge space while improving shared human-agent SA. To accomplish this we extended R-CAST, an agent-based Recognition-Primed Decision (RPD) model developed at the Pennsylvania State University (PSU) with the capability to interactively visualize the knowledge space during execution. Presented are the early results of a recently completed knowledge visualization experiment where ROTC cadets from the PSU operated the visually-enhanced R-CAST on a command and control simulation.

INTRODUCTION

From a military perspective, shared situation awareness (SA) is a critical tenet of Network Centric Operations (NCO) and has been the subject of much review [1, 2, 3]. A central premise of NCO is that while operating within the context of robust and networked physical, information, cognitive and social domains – the Warfigher of the future will be empowered to make better decisions. Recent operations in Iraq and Afghanistan have confirmed that in order to achieve effective Network-Centric Operations (NCO), innovative enhancements to military decision-making are desired. Required are processes and computational models that support the decision-makers' experience while promoting high levels of shared situation awareness (SA) – not only in the context of the external operating environment, but internally aligning the decision maker's mental model with the intelligent software agents working on their behalf.

One promising approach to this challenge has been Gary Klein's Recognition-Primed Decision (RPD) model [4]. Born out of the Naturalistic Decision Making (NDM) paradigm, RPD shares many of the characteristics found in NCO – requiring military commanders and their staff to operate in dynamic environments that are challenged with uncertainty, time stress, and high stakes outcomes. RPD is grounded in a requirement for strong SA and relies on one's experience to recognize the current situation in order to formulate *satisficing* courses of action. For complex military operations, like those being encountered in Operations Iraqi Freedom and Enduring Freedom (OIF/ OEF), challenges arise when the current situation is difficult to distinguish or slow to develop. The aim of this research is to integrate knowledge visualization into a computational RPD process in order to enhance the decision-maker's perception, comprehension, and projection of the underlying knowledge space while improving shared human-agent SA.

To accomplish this goal, we extended R-CAST, an agent-based RPD model developed at the Pennsylvania State University (PSU) with the capability to interactively visualize the knowledge or experience space during execution [5, 6]. In this context, knowledge visualization is defined as the mediating process that promotes the conveyance of experiential knowledge and higher-level SA between the cognitive-enabled RPD software agent and the decision maker. In this research we examine a knowledge visualization approach that reduces the high-dimensionality characteristics associated with an experience (knowledge) space onto a 2-dimensional display allowing transparency into the RPD decision process.

The remainder of this paper is organized as follows. In section 2, background information on the RPD-enabled R-CAST agent system and knowledge visualization is presented. In section 3, our research approach is outlined followed by a look at some early results of the experiment in section 4. Concluding remarks and future directions are given in section 5.

BACKGROUND

RPD-enhanced R-CAST Agent System

Differing from classical decision making where the decision maker attempts to optimize the expected value of a predetermined number of alternatives, the RPD model relies on intuition and experience along with mental simulation to recognize the similarity between the current situation and past experiences [4]. A *satisficing* solution based on that past experience is then quickly formulated. At a high level of abstraction, the model has two phases: recognition and evaluation. A diagram of the RPD process is shown in figure 1.

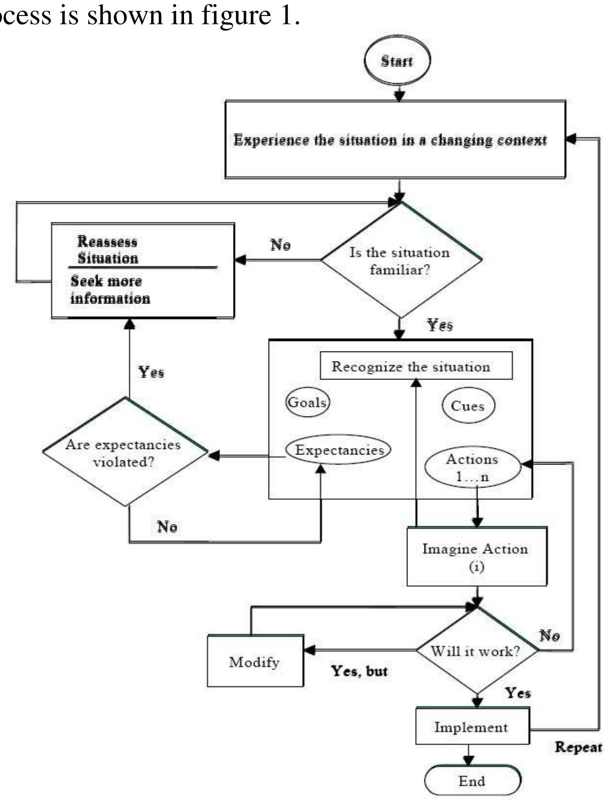

Figure 1: RPD Model

R-CAST is an agent-based, RPD-enhanced framework that extends the CAST (Collaborative Agents for Simulating Teamwork) agent architecture [5, 6, 7]. The R-CAST framework enables agents to collaborate with other members of the team (software or human) in sharing information relevant to their decision-makings based on the RPD paradigm. Leveraging the concept of shared mental models in team cognition, R-CAST proactively anticipates information needs and collaborates in seeking and monitoring relevant information effectively, allowing improved human-agent and agent-agent collaboration [8, 9].

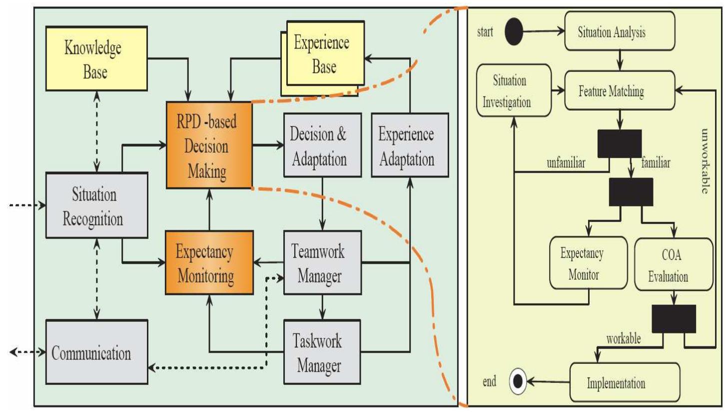

Figure 2: The R-CAST Architecture

Major components of R-CAST are shown in Figure 2. To capture the recognition phase in the RPD model, the *Decision Making* module uses the information in the *knowledge base*, past experiences from the *experience base*, and the current *situation recognition* to determine if a past experience matches the current situation. The evolution of decisions can involve inter-agent, intra-agent and human-agent activities, which are coordinated by the *Teamwork Manager* and *Taskwork Manager*, respectively [10].

The *Expectancy Monitoring* module monitors the current situational context for anticipated changes and informs the Decision Making module accordingly. Experiences that are adapted to a successful outcome are processed into the system as new experiences through the *Experience Adaptation Module*. Experiences are codified as cues, goals, courses of action and expectancies. In R-CAST the cues, goals and expectancies are represented as predicates [8].

Knowledge Visualization

Knowledge visualization is an emerging field growing out of the cognitive and computer sciences with an objective to facilitate the creation and transfer of knowledge between two or more entities [11]. Differing from traditional information visualization, knowledge visualization is more than facts and graphs, its goal is an enabling technology allowing the correct conveyance and application of complex insights, experiences, perspectives, and high-level concepts from one entity to another [12, 13].

On one level, visualization can be thought of as a dimension-reduction activity designed to summarize complexity and encourage the influence of human visual perception into the decision making process [14, 15]. Visualization takes advantage of the human capacity for spatial reasoning and the development of mental or concept maps of complex relationships [16, 17]. It is through this visual construct that the human is able to project relationships and association among the visualized objects and ultimately align the transfer and creation of knowledge. The goal of introducing knowledge visualization into the RPD process is to enhance the decision maker's understanding of the underlying decision space – supporting the collaboration and improving the shared SA between the human operator and its cognitive-enabled software agents.

The knowledge visualization approach adopted for this research is based on a hybrid multidimensional scaling (MDS) technique. MDS is a statistical method that allows a matrix of similarities or dissimilarities measures to be dimensionally reduced to a human understandable 2– or 3–dimensional space [18]. In this experiment it is the codified *experiences* of the decision space that make up the similarity matrix in question. Similarity calculations between independent experiences are based on the aggregated features that define each experience.

Shown in figure 3 is an example of an R-CAST knowledge Visualization of the Agent Decision Space (VADS). The VADS is a visual display used to map a collection of past *experiences* or Common Historical Cases (CHCs). The positioning of the CHCs circles are based on relative similarities and mapped via an MDS-type procedure. As a new situation unfolds, a target icon is positioned on the VADS relative to the similarity of closest matching CHC.

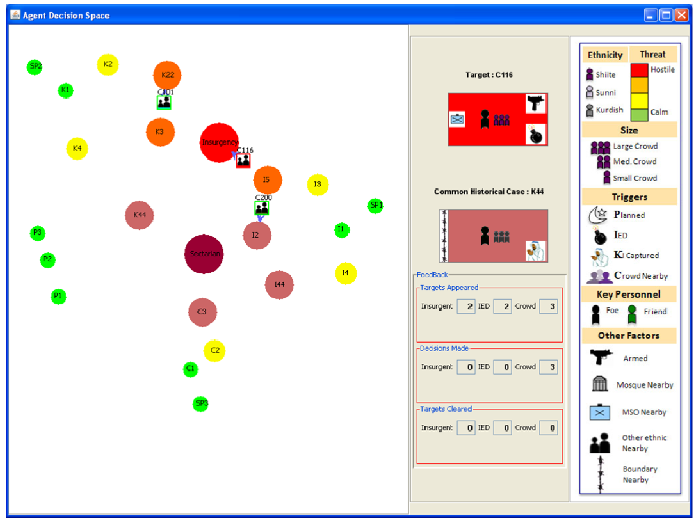

Figure 3: R-CAST Visualization Agent Decision Space (VADS)

For this experiment, our VADS implementation was used to represent crowd experiences; specifically:

- IED-related crowd experiences,
- Key-insurgent related crowd experiences,
- Planned crowd related experiences and
- Other crowd-on-crowd related experiences.

The size, color and position of the crowd CHC icons were determined using the following characteristics:

- crowd triggering event,
- crowd size,
- crowd composition,
- crowd proximity to military significant objects,
- crowd proximity to civilian significant objects,
- hostility level,
- level of armament, and
- anticipated threat level (low, medium, high, very high).

Generally, the darker and larger the CHC icon the higher the level of importance. The two areas of greatest concern are the two large centered CHC icons representing experiences associated with Insurgency and Sectarian Violence. As the characteristics of an active crowd changes, it is repositioned on the ADS display. In addition to temporally repositioning active crowd targets on the ADS, the conveyance of knowledge about an active crowd or a related CHC is augmented with the use of iconic symbols located on the right of the display. Mousing over a CHC or clicking an active target refreshes appropriate icon display. An example of a crowd information icon is shown in figure 4.

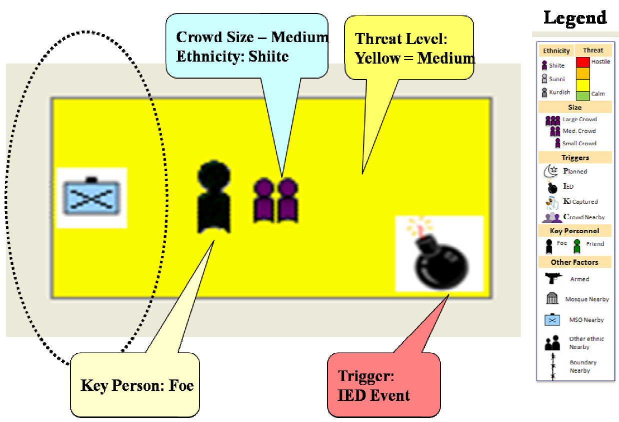

Figure 4: Experience Icon

Allowing holistic view of the ADS provides a transparent view of the agent decision process improving the decision makers shared SA allowing for adjustment of contextual constraints and ability to prioritizing missing information.

RESEACH APPROACH

Simulation Environment

In order to exercise our knowledge visualization concepts we utilized a simulation environment developed collaboratively between the PSU and the U.S. Army Research Laboratory (ARL) – namely the "Three-Block Challenge". Three-Block Challenge is a human-in-the-loop command and control (C2) simulation involving an urban setting where the context of the current mission frequently switches between humanitarian, peacekeeping and combat operations. The context switching imposes challenging information and decision making demands found in an urban C2 operation.

Our synthetic environment supports a C2 team consisting of an S2 (intelligence officer) and an S3 (operations officer). Each officer is assisted by an RPD-enabled software agent. The S2 officer is responsible for processing incoming Spot reports, collecting relevant information for other sources and alerting the S3 to potential threats. The S3 is responsible for processing alerts from the S2 and making decisions on which targets to address and determine the resource allocation (friendly units). The simulation generates three kinds of threat objects: improvised explosive devices (IEDs), crowds and insurgents. Each of the threat objects is synchronized by the simulation engine as SPOT reports. Other objects of interest in the environment include main supply routes (MSRs), key buildings (religious, schools and hospitals) and military significant objects (MSOs) including check points, garrisons, police stations and other government buildings.

For this study the roles of the officers have been simplified. The actions of the S2 have been completely automated by a suite of S2 RPD agents allowing us focus entirely on the S3 decision making process. Decisions by the S3 officer involving target selection and resource allocation require trade-offs among multiple factors: target type, available units, unit distance, threat level and remaining life of target. Figure 5 shows a concept of operations for the planned experiment.

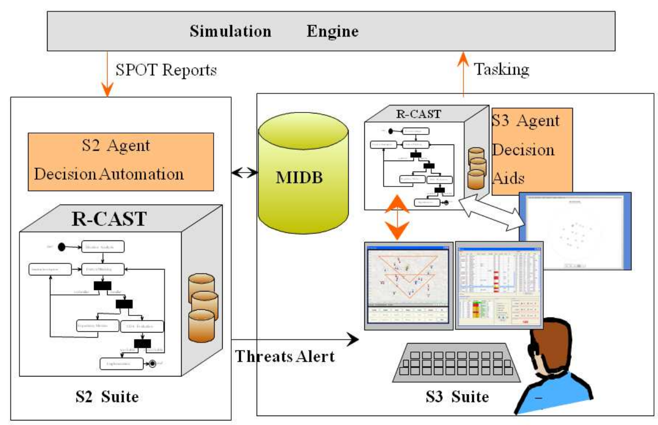

Figure 5 : Knowledge Visualizaiton Concept of Operation

Experiment Objective

The objective of this year's research effort was to assess the effects of integrating knowledge visualization into a cognitively-enabled agent-based decision support system on the human subject's situation awareness, task performance, mental workload and trust. As in previous studies, our study utilized the R-CAST agent architecture and the Three-block Challenge simulation environment.

Design

The study employed a 2 (visualization mode) x 2 (work load) x 2 (task complexity) mixed design. The between-group factor was the mode of visualization (experimental group utilizing knowledge visualization vs. control group utilizing tradition table visualization). The two within-group factors were the scenarios' work load (5 crowds vs 10 crowds) and level of task complexity (ratio of fast-burning vs slow-burning crowd movement). The dependent variables included task performance, situation awareness, trust in automation, and subjective workload.

Experimental Interface

For this year's experiment the dual-display R-CAST user interface was modified to incorporate the knowledge visualization concept previously described.

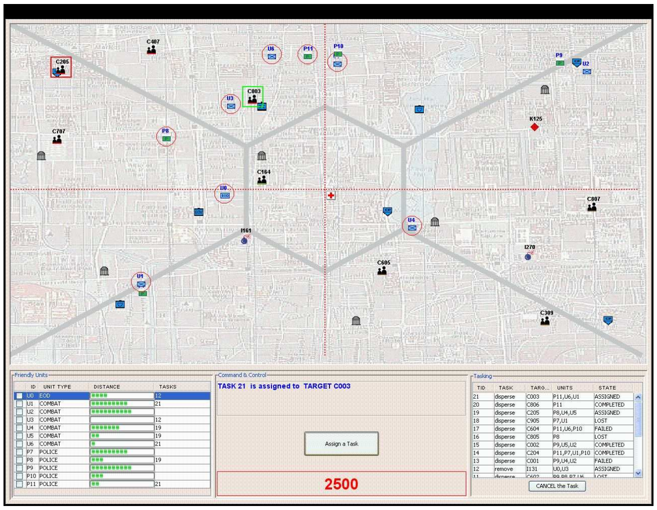

Figure 6: R--CAST Military Geo-Spatial Map

Both the experimental group and control group continued to have access to the Military Geo-Spatial map (Geo-Map) shown in figure 6. The Geo-Map provides the common operating picture (COP) to the simulation environment: showing all active icons (friendly and hostile), unit status, tasking assignments and game score.

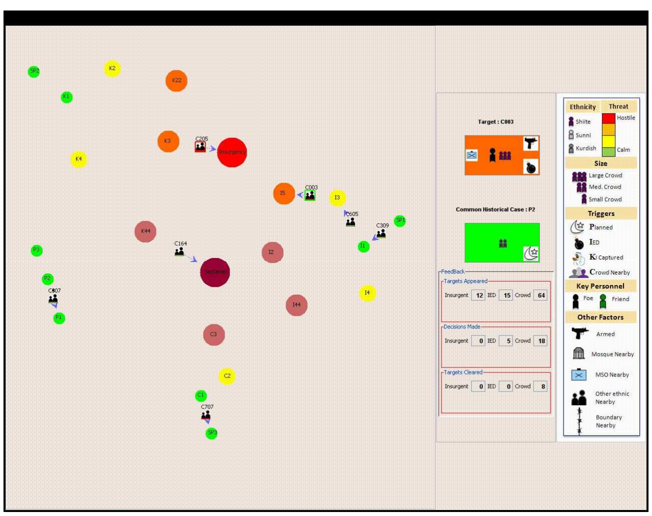

Figure 7: R-CAST Visualization Agent Decision Space.

To introduce the concept of knowledge visualization, we modified the focus of this year's experiment to emphasize the importance of crowd control. For the experimental group the VADS display was used to convey the underlying agent decision process (figure 7). For the control group a tabular form of the same information was given in the Agent Decision Table (ADT) shown in figure 8.

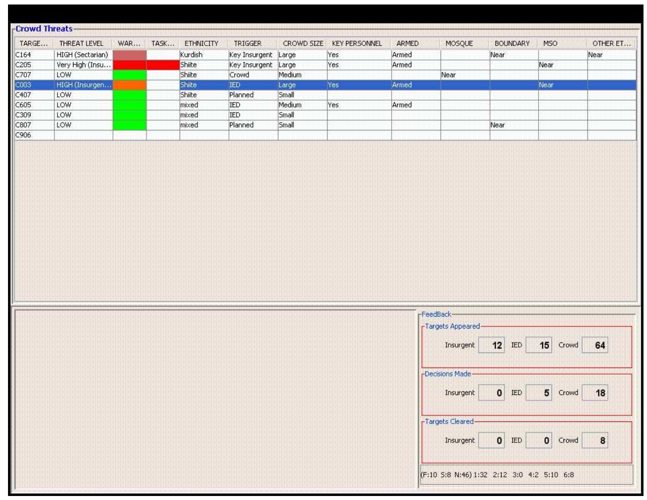

Figure 8: RCAST Visualization Agent Decision Table

Participants

Thirty two ROTC students from the PSU (29 male, 3 female; mean age 20.0) participated in this study for a nominal financial payment. The experimental group had 15 males and 1 female with an average video game experience of 4.0 hours per week while the control group contained 14 males and 2 females with an average video game experience of 4.3 hours per week.

Scenario Development

Four 10-minute scenarios were developed for this experiment, manipulating the work load and level of task complexity. The work load was defined by the number of active crowds on the display. We defined two levels: Low (5 active crowds at one time) and High (10 active crowds at one time). For task complexity we altered the ratio of slow-burning crowds to fast-burning crowds. Slow-burning crowds were defined as crowds taking more than 60 seconds to reach threat-level 4 (the highest level) while fast-burning crowds had the potential to reach threat-level 4 under 60 seconds. The ratio of slow-burning to fast-burning was adjusted from 1:1 to 1:2. Scenarios also varied in the location and shapes of main supply routes, key buildings, and military significant objects.

EARLY RESULTS

During the experiment numerous measurements were made. Assessment of task performance for each scenario was measured by scoring number of targets successfully cleared (more points being awarded for higher threat crowds). Assessment of SA was capture during and after each scenario using the Situation Awareness Global Assessment Technique (SAGAT) [19]. Participant's perceived workload was assessed using NASA-TLX [20]. A trust in automation scale developed by [20] was administered following completion of the final scenario.

Two analyses of task performance and real-time SA have been performed. The results indicate positive step towards aligning the decision maker understands with the software agents working on their behalf. Detailed analysis on higher-level SA including comprehension and projection are underway.

Task Performance

One of the measures calculated for task performance was the combined Score*real-time SAGAT. The un-normalized result for this t-test measure showed the experimental group score on average 20 percent improved over the control group with a statistical p value = .0719.

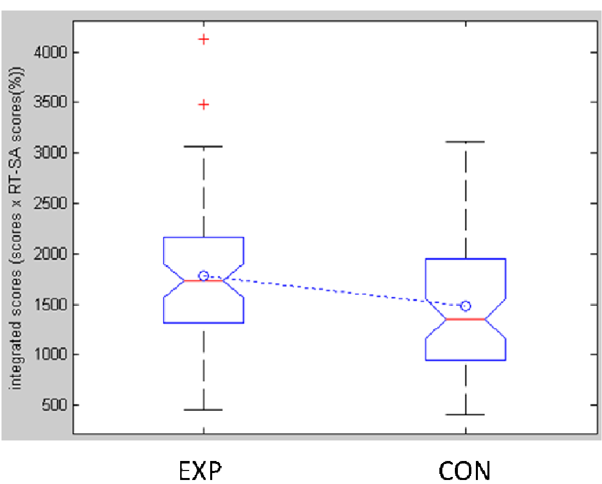

Figure 9: Task Performance - Score * Real-time SA

Real-time SA

To measure real-time SA participants were ask a SAGAT question after each assignment of resources to a threat target. Here the results of the t-test show SA improved with the experimental group by about 8 percent on average over the control group with a statistical p value = .1424.

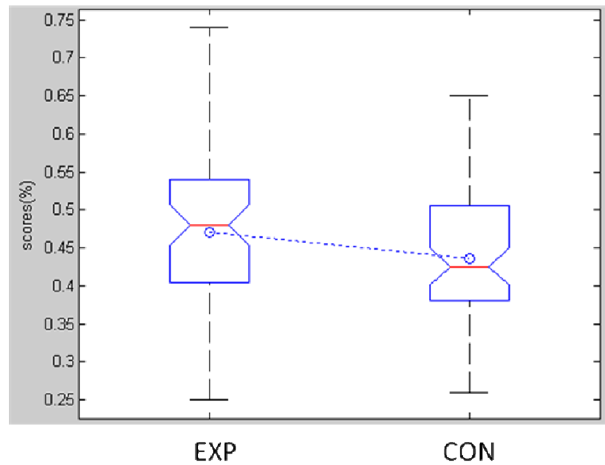

Figure 10: Real-time SA Score

CONCLUSIONS

As the Army grows towards the realization of true NCO the requirement for effective cognitive-enabled decision aids grows with it. Enabling technologies that allow the conveyance of knowledge (complex insights, experiences, and high-level concepts) including shared SA and its correct application will be critical. In this research we examined a knowledge visualization approach designed to enhance the decision maker's perception, comprehension, and projection of the underlying knowledge space while improving shared human-agent SA. The preliminary results reveal progress has been made, with much work remaining.

ACKNOWLEGEMENT

This research was supported by participation in the Advanced Decision Architectures Collaborative Technology Alliance sponsored by the U.S. Army Research Laboratory under Cooperative Agreement DAAD19-01-2-0009.

References

[1] Leedom, D.K. (2001). *Final Report: Sensemaking Symposium*. (Technical Report prepared under contract for Office of Assistant Secretary of Defense for Command, Control, Communications & Intelligence). Vienna, VA: Evidence Based Research. Inc.

[2] Garstka, J. and Alberts, D. (2004). Network Centric Operations Conceptual Framework Version 2.0, U.S. Office of Force Transformation and Office of the Assistant Secretary of Defense for Networks and Information Integration.

[3] Wilson, Clay. "Network Centric Warfare: Background and Oversight Issues for Congress." CRS Report for Congress, 2 June 2004.

[4] Klein, G. A., Recognition-primed decisions. In W. B. Rouse, editor, Advances in man-machine systems research, volume 5, pages 47{92. Greenwich, CT: JAI Press, 1989.

[5] Fan, X., and Yen, J., R-CAST: Integrating Team Intelligence for Human-Centered Teamwork. *Proc. of the Twenty-Second AAAI Conference on Artificial Intelligence (AAAI-07)*, 2007.

[6] Yen, J., Fan, X., Sun, S., Hanratty, T., and Dumer, J., Agents with shared mental models for enhancing team decision-makings. *Decision Support Systems, Special issue on Intelligence and Security Informatics,* 2005.

[7] J. Yen, J. Yin, T. Ioerger, M. Miller, D. Xu, and R. Volz. Cast: Collaborative agents for simulating teamworks. In *Proceedings of IJCAI'2001*, pages 1135{1142, 2001.

[8] Fan, Sun, McNeese, and Yen, Extending Recognition-Primed Decision Model For Human-Agent Collaboration, In Proceedings of *the Fourth International Joint Conference on Autonomous Agents and Multi Agent Systems*, pp. 945-952, The Netherlands, July 25-29, 2005

[9] Hanratty, T., Dumer, J., Yen, J., and Fan, X, Using Agents with Shared Mental Model to Support Objective Force, in *Proceedings of the 7th World Multi-conference on Systemics, Cybernetics and Informatics (SCI 2003)*, Orlando, USA, July 27-30, 2003

[10] Fan, X., B. Sun, S. Sun, M. McNeese, J. Yen, R.Jones, T. Hanratty, and L. Allender., RPD-Enabled Agents Teaming with Humans for Multi-Context Decision Making, *In Proceedings of the Fifth International Joint Conference on Autonomous Agents and Multi-Agent Systems (AAMAS'06)*, pages 34--41, May 8-12, Japan, 2006.

[11] Eppler, M. and Burkhard, R., (2007), "Visual Representation in Knowledge Management: Framework and Cases", *Journal of Knowledge Management*, Vol. 11, No. 4, pp. 112-122

[12] Burkhard R. Towards a framework and a model for knowledge visualization: synergies between information and knowledge visualization. In: Tergan S-O, Keller T, (Eds). Knowledge and Information Visualization: Searching for Synergies. Lecture Notes in Computer Science, Vol. 3426. Springer-Verlag: Heidelberg. 2005.

[13] Burkhard, R., & Meier, M. (2004). *Tube map: Evaluation of a visual metaphor for interfunctional communication of complex projects.* Paper presented at the I-KNOW '04, Austria.

[14] Card, S., Mackinlay, J., Shneiderman, B., Readings in information visualization: using vision to think, Morgan Kaufmann Publishers Inc., San Francisco, CA, 1999.

[15] Shneiderman, B., Designing the User Interface: Strategies for Effective Human-Computer Interaction, Addison-Wesley Longman Publishing Co., Inc., Boston, MA, 1997.

[16] Börner, K., Chen, C., & Boyack, K., (2003), Visualizing Knowledge Domains, In Blaise Cronin (Ed.), *Annual Review of Information Science & Technology*, Volume 37,Medford, NJ: Information Today, Inc./American Society for Information Science and Technology,chapter 5, pp. 179-255, 2003.

[17] Heer, J., Card, S., Landay, J., (2005), prefuse: a toolkit for interactive information visualization, Proceedings of the SIGCHI conference on Human factors in computing systems, April 02-07, 2005, Portland, Oregon, USA.

[18] Cox, T. F., and Cox, M. A. A. [2001]. *Multidimensional Scaling,* 2nd Edition. Washington, D.C.: Chapman & Hall/CRC.

[19] Endsley, M.R. (1995). Measurement of situation awareness in dynamic systems. *Human Factors, 37*(1), 65-84.

[20]Hart, S. G. & Staveland, L. E. (1988). Development of the NASA-TLX (Task Load Index): Results of empirical and theoretical research. In P. A. Hancock & N. Meshkati (Eds.), *Human mental workload* (pp. 139-183). North-Holland: Elsevier Science.

[21] Jian, J-Y., Bisantz, A. M., & Drury, C. G. (2000). Foundations for an empirically determined scale of trust in automated systems. *International Journal of Cognitive Ergonomics, 4* (1), 53-71.