

12th International Command and Control Research and Technology Symposium
“Adapting C2 to the 21st Century”

Paper Number: I-166

**Using the Dynamic Model of Situated Cognition to Assess
Network Centric Warfare in Field Settings**

Lawrence G. Shattuck
Naval Postgraduate School
Operations Research Department
Monterey, CA 93943
Tel: (831) 656-2473
Fax: (831) 656-2595
lgshattu@nps.edu

Nita Lewis Miller
Naval Postgraduate School
Operations Research Department
Monterey, CA 93943
nlmiller@nps.edu

Gregory A. Miller
Naval Postgraduate School
Systems Engineering Department
Monterey, CA 93943
gammer@nps.edu

12th International Command and Control Research and Technology Symposium
“Adapting C2 to the 21st Century”

**Using the Dynamic Model of Situated Cognition to Assess
Network Centric Warfare in Field Settings**

Lawrence G. Shattuck
Naval Postgraduate School
Operations Research Department
Monterey, CA 93943
lgshattu@nps.edu

Nita Lewis Miller
Naval Postgraduate School
Operations Research Department
Monterey, CA 93943
nlmiller@nps.edu

Gregory A. Miller
Naval Postgraduate School
Systems Engineering Department
Monterey, CA 93943
gammer@nps.edu

Abstract

Over the past three years, we have presented several papers on a model of data and information flow through a system: the Dynamic Model of Situated Cognition (DMSC). The DMSC has proved useful in a variety of settings: modeling individual performance, military C2, naval operations, human error in military mishaps, team behaviors in complex organizations and, most recently serving as an aid to system designers. Although first proposed as a conceptual model, the DMSC can also be used to assess the flow of data and information in a dynamic field setting, the Tactical Network Topology (TNT) Project. The TNT project is a series of ongoing war-gaming field studies conducted quarterly by the Naval Postgraduate School and held at a variety of operational venues. The current research involved 12 trials in which four mock enemy vehicles attempted to infiltrate a specified region. Unmanned aerial vehicles (UAVs) were used as the primary sensor platform for the simulated Joint Force. GPS data for enemy vehicles and friendly UAVs, and audio and video tapes of the tactical operations center (TOC) were recorded and used to populate the DMSC. This study validates the utility of the model, extending its use to field settings.

Introduction

The concept of network Centric Warfare (NCW) has been in existence for more than ten years (Cebrowski & Garstka, 1998). Over the last decade, NCW proponents have challenged both U.S. and allied defense organizations to revolutionize their concepts and practices of military command and control. NCW tenets have been developed and promulgated. Books have been published. Numerous symposia have been conducted. Hundreds of researchers have been funded. Much of the effort put forth by NCW enthusiasts has been focused on technology. Improvements in bandwidth, connectivity, and processing speed have moved us closer to the time where military practitioners of all services, in every part of the battlespace, will have access to the same data. While such capability fulfills a portion of the tenets of NCW, it does not necessarily follow that these technological improvements will lead to achievement of the other tenets.

The tenets of Network Centric Warfare are as follows (Alberts, 1996).

1. A robustly networked force improves information sharing.
2. Information sharing and collaboration enhance the quality of information and shared situational awareness.
3. Shared situational awareness enables self-synchronization.
4. These, in turn, dramatically increase mission effectiveness.

At least some of the phrases within the NCW tenets suggest technological solutions: a robustly networked force; information sharing; shared situational awareness; and self-synchronization. It is reasonable for organizations to justify their research and development of technological systems based on these tenets. However, while technology can be used to *aid* the activities listed in the tenets, many of these activities are fundamentally human endeavors. Information sharing among military organizations facilitates collaboration and is essential to warfighters having shared situation awareness. And, shared situation awareness leads to the ability of warfighters to synchronize their activities.

Focusing on technological solutions with little consideration for the capabilities and limitations of the warfighters is imprudent. Yet, this is often the case. The result is that these novel technologies provide capabilities not needed by warfighters or they function in ways that are not compatible with warfighters. These solutions will quickly fall into disuse or will distract warfighters from the tasks that are truly important for mission accomplishment. Equally unacceptable is the narrow focus of some psychologists on cognitive processes of the humans without considering the military context or the technologies with which the warfighters must interact. While these researchers may gain valuable insights into human cognition, their findings by themselves may have limited applicability to warfighting. These findings must be shared with technologists who can then incorporate them into the design of new systems. Thus, cooperation and collaboration between technologists and psychologists or human performance experts are critical to the success of NCW.

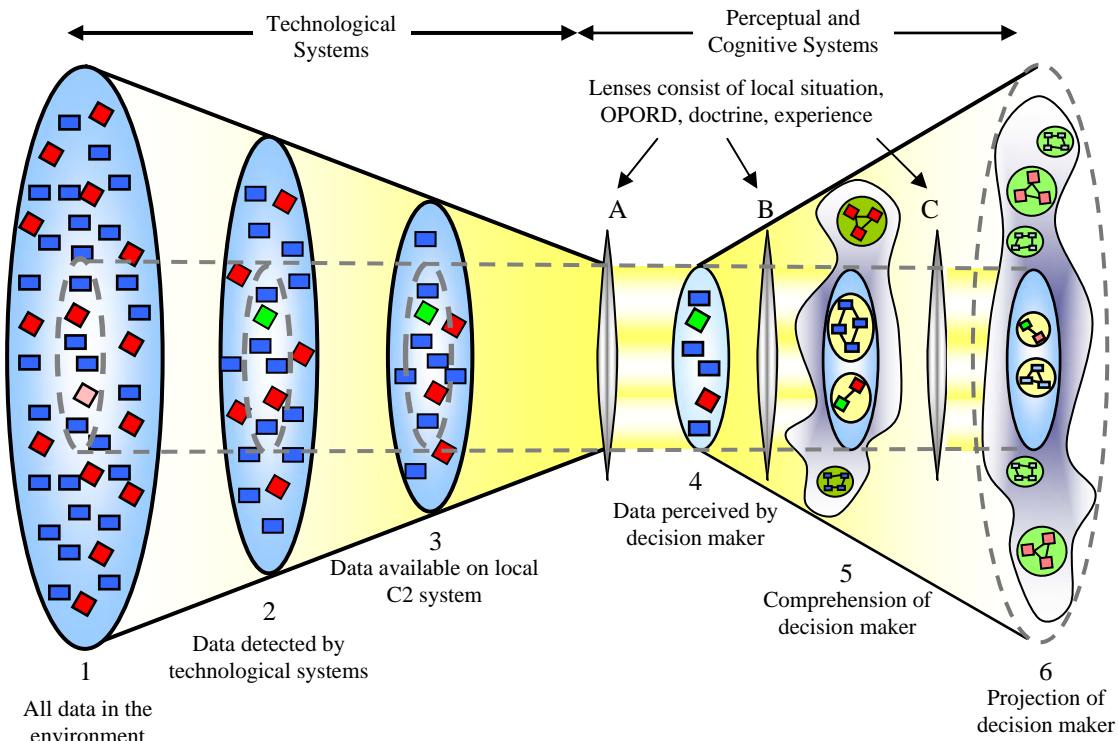
The Dynamic Model of Situated Cognition (DMSC) has successfully integrated technological and human elements into a single conceptual framework (Miller & Shattuck, 2004a; 2006). This model describes the interaction between technological and human agents in complex systems. It has been used retrospectively to explain how activities can go awry in complex systems (Shattuck & Miller, 2006). Tracing the flow of events through the model often reveals that, whereas the initial finding may be ‘human error,’ the actual cause may be rooted in the technology. The model also has been used as an analytical framework for military command and control (C2) simulation experiments (Miller & Shattuck, 2004b). The present paper extends the use of the model to field experimentation. The authors discuss the challenges and the benefits of using the model in dynamic settings.

The Dynamic Model of Situated Cognition

The model grew out of a command, control, communications, computers, intelligence, surveillance, and reconnaissance (C4ISR) war game conducted at FT Knox in the Army’s Unit of Action Mounted Battle Laboratory (UAMBL). In that exercise it was apparent that the research analysts were divided into two camps: those focused on the technological aspects of the simulation and those focused on the human participants in the system. Although the two groups used the same terms (i.e., situation awareness), it became apparent that they defined the term in very different ways. The model, then, emerged as an attempt to define a common framework with which the groups could communicate effectively.

The Dynamic Model of Situated Cognition has been described elsewhere in detail (Miller & Shattuck, 2004a; 2004b; Miller & Shattuck, 2005; Shattuck & Miller, 2006). A brief description of the model is presented here. The model consists of six ovals of varying sizes and three lenses (see Figure 1). The three ovals on the left side of the model (1, 2 and 3) represent the technological side of a system while the three ovals on the right (4, 5 and 6) represent the human perceptual and cognitive processes. Oval 1 is ground truth and in the simulated laboratory scenarios where it was first used, contains all the data concerning enemy and friendly forces, terrain features, weather conditions, non-combatants, and even the intentions of those human entities in the battlespace.

Oval 2 is a subset of Oval 1, and includes only those entities that are detected by sensor systems. It does not include everything in Oval 1 because there may not be enough sensors to cover the battlespace, they may be in the wrong place, they may be in the wrong mode (i.e., 1 meter vs. 3 meter resolution), or they may be inoperative. Oval 2 is the first point at which error may be introduced into the model. A flawed sensor algorithm may cause an entity to be misidentified. For example, in Figure 1, a red enemy entity in Oval 1 is detected and classified as a green neutral element by the sensor network and that misidentification is propagated through the remainder of the model. Alternatively, the pink entity in Oval 1 is an enemy decoy but the sensor is unable to discriminate between a decoy and an actual enemy vehicle. The technological system classifies it as an enemy entity and propagates that representation through the model.



© Miller and Shattuck, 2003

Figure 1. Dynamic Model of Situated Cognition

Oval 3 depicts the data displayed at the command and control workstation of the individual operator. These displays may be visual, auditory, or tactile. Many displays can be tailored by the users and, as such, the type and amount of data displayed may vary greatly over time. Ovals 4, 5 and 6 on the right side of the model represent, respectively, the *perception* of data elements, the *comprehension* of the current situation (sometimes called a mental model) and the individual's *projection* of current events into the future. These three ovals correspond to situational awareness Levels 1, 2, and 3 in the scientific literature (Endsley, 2000).

The lenses in the Dynamic Model of Situated Cognition reflect the knowledge, attributes, and attitudes that reside in the decision maker. Although the elements contained in each of the three lenses is the same, the placement of the lenses in the model indicates that different functions are performed by each lens. Lens A, the lens between Ovals 3 and 4, directs attention to selected incoming stimuli. Lens B, between Ovals 4 and 5, influences how data are organized into information. Lens C, between Ovals 5 and 6, guides the process of extrapolating current information into predictions about the future. In addition, the lenses are highly dynamic, and vary from person to person, continually being influenced by incoming information, new experiences, and variations in the physiological and psychological states of the individual.

There are at least six classes of information embedded in the lenses. *Individual states and traits* represent those relatively enduring (e.g., intelligence or personality) and transient (e.g., fatigue) characteristics of an individual that affect decision making. *Social factors* include issues ranging from small group dynamics to cultural differences that might exist among decision makers. The *local context* influences the data to which a decision maker will attend. The *plan* represents the specific goals to be achieved and the means by which they will be achieved. *Guidelines* represent general procedures to which decision makers may refer if the plan is underspecified. *Experience* refers to previous activities in which a decision maker has engaged.

As is the case with the human visual lens, perceptual distortions may result from asymmetries (see Figure 2). Distortions in the lens preceding the perceptual oval (Lens A) may divert the attention of the decision maker away from the most important or relevant data. Distortion in the other two lenses (Lens B and C) can result in an inaccurate mental model of the current situation and false expectations about the future. Figure 2 also depicts feedback loops from Oval 5 (Comprehension) to each of the preceding ovals and to the three lenses. (Not shown, but also included in the model are feedback loops from Oval 6 (Projection) to the five preceding ovals and to the three lenses.)

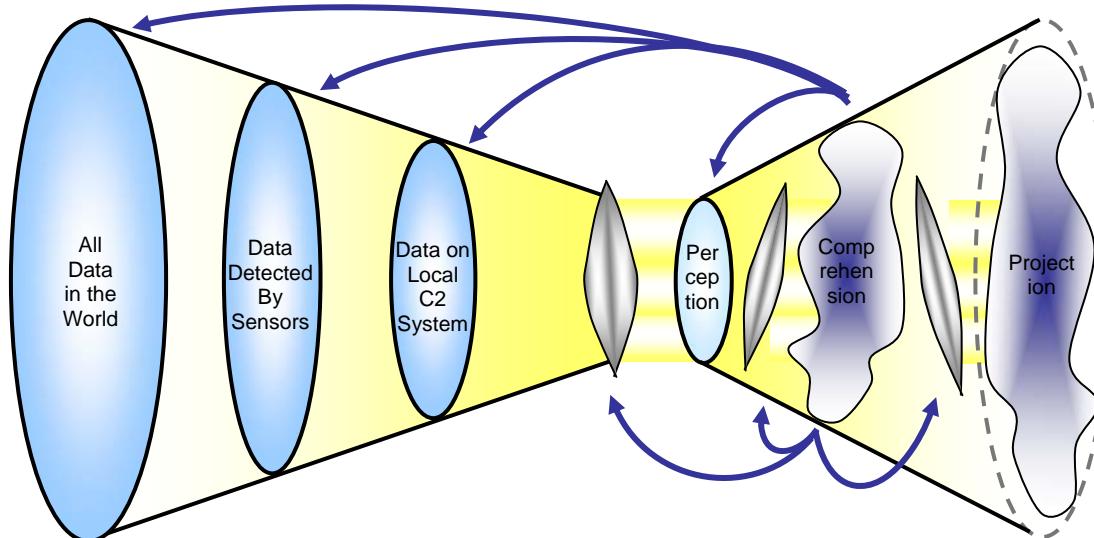


Figure 2. Distortions in the lenses lead to inaccurate perceptions, comprehensions, and projections. Feedback loops in the model represent decisions and updates to the lenses.

The following example illustrates the data and information flow through the model and the role of the feedback loops. There is an enemy unit moving through the battlespace (Oval 1) but it has not yet been detected. At some point, sensors detect the motion of the enemy (Oval 2). Data from the sensors are sent to the friendly unit and appear on the decision maker's workstation (Oval 3). If the workstation is configured properly and the decision maker is attending to the workstation (based on contents of Lens A), the data may be perceived (Oval 4). The decision maker may determine (Oval 5) there is an enemy of unknown size and strength on the battlefield based on the local context and his

or her experience (as well as other contents of the Lens B). Given that comprehension and knowledge of enemy doctrine (as well as other contents of Lens C), the decision maker may expect or project (Oval 6) the enemy to be of a certain size and move in a particular direction. Having made that projection, the decision maker may elect to reposition an unmanned aerial vehicle (UAV) to more closely monitor the enemy unit. This decision is represented by the feedback loop from Oval 6 to Oval 1. Once the UAV arrives on station, the sensors on board provide additional data, which flow from Oval 2 to Ovals 3, 4, 5, and 6. The additional data from the UAV sensors will either confirm or correct the earlier comprehension and projection.

Tactical Network Topology (TNT) Field Studies

Each academic quarter, the Naval Postgraduate School (NPS) conducts a week-long field exercise at Camp Roberts, a California Army National Guard installation just north of Paso Robles, CA. The exercises are sponsored by Special Operations Command (SOCOM) and are referred to as Tactical Network Topology (TNT) experiments after the communication infrastructure that supports the activity. The TNT exercises provide excellent opportunities for NPS faculty and students (and selected organizations external to NPS) to test novel hardware or software applications in a field setting. As such, the TNTs are often a collection of demonstrations rather than scientific experiments. Nevertheless, the field setting, coupled with realistic scenarios, provides an attractive alternative to strictly controlled laboratory or computer-based simulation activities.

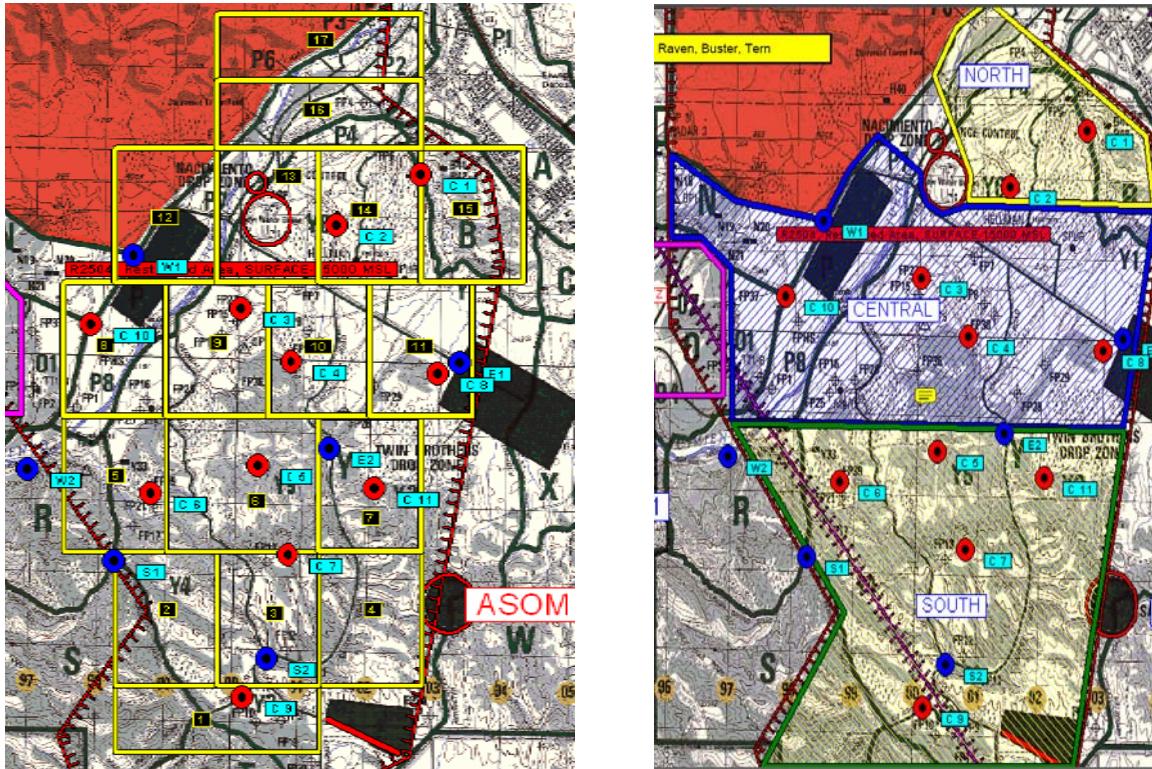
TNT 07-1 was conducted from October 27 – November 3, 2006. Three days were dedicated to comparing two methods for conducting searches with unmanned aerial vehicles (UAVs). NPS researchers developed an Aerial Search Optimization Model (ASOM). Their model identifies the optimal search patterns based on the number and type of UAVs available, and also considers logistical, operational, terrain, and intelligence inputs. Performance on a detection task while using ASOM was compared with performance on a manual (non-ASOM) search strategy based on doctrinal principles for employment of UAVs. Figures 3a, 3b, and 3c are photos of the three different UAVs used in this field experiment. They are relatively small and have a limited payload (i.e., a video camera with tilt, pan, and zoom capabilities). They were chosen because they are representative of UAVs currently being used by company- and platoon-sized units in coalition operations around the world.



Figures 3a – 3c. Photos of the UAVs flown in support of TNT 07-1. Figure 3a (left) is a Buster UAV; Figure 3b (center) is a Raven UAV; Figure 3c (right) is a Tern UAV.

A total of 12 runs were completed, six ASOM and six non-ASOM. Each run was 48 minutes in length. The scenarios for all 12 runs were similar. The UAVs were employed to detect and identify four enemy vehicles moving through the Camp Roberts terrain. The vehicles had entered the area through a checkpoint but shortly after being processed, a routine database check had revealed that the vehicles contained suspected enemy personnel who were wanted for questioning. The UAVs were launched in an attempt to locate the vehicles. There were from one to three UAVs available to conduct the search. There were six checkpoints (two in the west, two in the south, and two in the east) that could be used. And, there were 20 possible destinations for the four enemy vehicles. Each run started after the enemy vehicles passed through the designated checkpoint. Eight minutes later, the UAVs were released to begin the search. The run concluded 40 minutes later or after all enemy vehicles had been detected and identified, whichever happened sooner. The enemy vehicles were sport utility vehicles (SUVs) with marker panels affixed to their roofs to facilitate identification. When an enemy vehicle was positively identified, the driver of that vehicle was instructed (via radio) to pull off the road and open the vehicle's doors. This procedure was implemented in order to minimize the number of multiple detections.

Prior to the TNT, the researchers divided the Camp Roberts terrain into 17 ASOM segments (see Figure 4a). Prior to an ASOM run, the researchers were told the type and number of UAVs that were to be available and the entry point for the enemy vehicles. Their model then generated a search pattern for each of the UAVs in the form of a sequence of segments.



Figures 4a and 4b. Map on the left shows the Camp Roberts terrain overlaid with the 17 ASOM segments (4a); map on the right shows the three non-ASOM search areas (4b).

The non-ASOM searches were conducted by dividing the Camp Roberts terrain into three areas - north, central, and south (see Figure 4b). These manual searches were conducted at the discretion of experienced UAV operators and according to the following doctrinal principles.

- Within the first 10 minutes of the event, bias the search toward the sub-area near the suspected enemy point of entry.
- Within the next 20 minutes, bias the search of the sub-area towards the areas of known High Value Targets (HVTs).
- During the last 10 minutes, bias the search of the sub-area towards the direction of potential threat exit.
- Actual method/technique (road following, bow tie, linear, etc.) of search is at the discretion of the UAV operators and per their specific UAV SOPs.

For each ASOM run there was a corresponding non-ASOM run. These paired runs were identical with respect to the UAVs available for the search, the point of entry of the suspected enemy vehicles, and the destination of the vehicles. The order of the runs was randomized. Key players in these runs included the Tactical Operations Center (TOC) commander, the air boss, the two UAV video feed observers in the TOC, the UAV operators in the field, and the red team commander. The TNT mesh network carried the live video feed from the UAVs to the TOC. The role of the TOC commander was supervisory in nature. The air boss communicated directly with the three UAV ground control units (GCUs) and directed the administrative and operational activities of the UAVs, including search patterns. The UAV operators at the GCUs and the video feed observers in the TOC were responsible for detecting and identifying the suspected enemy vehicles. The red team commander directed the activities of the four enemy ground vehicles.



Figures 5a and 5b. Photo on the left (5a) shows the work area of the air boss; photo on the right (5b) shows the work area of the video feed observers in the TNT tactical operations center.

Employing the Dynamic Model of Situated Cognition in a Field Setting

Prior to TNT 07-1, the authors of this paper used the Dynamic Model of Situated Cognition (DMSC) to analyze data generated by simulated command and control

exercises. In these studies, data generated by the simulation (and stored in memory) and the voice transcripts of the participants were used afterward to populate the ovals of the model. Since the TNT exercises are field studies, there is no single source from which to extract the data. Therefore, the authors of this paper had to coordinate with TNT exercise planners beforehand to identify various sources of data that could be collected and used to populate the ovals of the DMSC.

All UAVs and enemy ground vehicles were equipped with global positioning system (GPS) tracking devices. Positions were recorded and stored once every second. (In addition to knowing the positions of the UAVs, the technology made it possible to reconstruct the footprint of each UAV camera as it searched the terrain below.) In the TOC, video feed observers typed their comments and observations into a time-stamped digital log. Activities in the TOC were also recorded with a digital video camera. Digital voice recorders were placed on the TOC commander, the air boss, the TOC video feed observers, and the red team commander. At the conclusion of TNT 07-1, GPS data were collected and analyzed, and a portion of the more than 50 hours of voice recordings were transcribed.

At the conclusion of the TNT exercise, the authors used the GPS data and digital recording transcriptions to reconstruct the flow of data through the Dynamic Model of Situated Cognition. The purpose of this analysis was to determine what data were present in the technological portion of the system (i.e., the left side of the model) and what data were actually detected and processed by the humans in the system (i.e., the right side of the model). The results will be used to improve the TNT infrastructure, displays, and configuration of the TOC for future exercises.

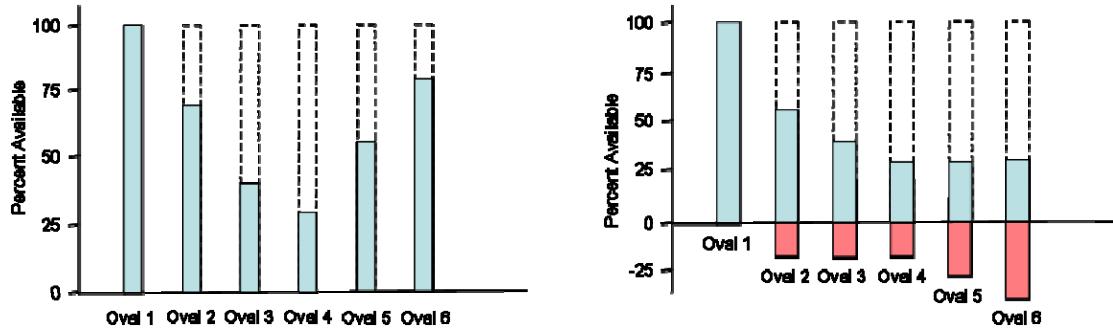


Figure 6a and 6b. Graph on the left (6a) depicts the hypothetical flow of data through the DMSC in an optimal way; graph on the right (6b) depicts the flow in a dysfunctional way.

Figure 6a depicts the hypothetical profile of data flowing through the DMSC. As stated earlier, Oval 1 includes all data (i.e., 100%) in the environment. The column for Oval 2 indicates that less than 75% of the data in Oval 1 are detected. Approximately 40% of the data proceed to Oval 3 (C2 workstations) and less than 30% make it to Oval 4 (perception). The column in Oval 5 (comprehension) has the potential to be larger than the preceding two columns because decision makers may combine what they have

perceived with their experience and their understanding of both the situation and doctrine. The result is that their mental model of the situation may be a closer approximation of what is in Oval 1 than would be possible without the contents of the lens. The same process occurs from Oval 5 to Oval 6 (projection). An accurate comprehension coupled with an accurate lens will facilitate a projection that closely approximates the contents of Oval 1.

Figure 6b depicts another possible flow through the model. In this scenario, erroneous data enter at Oval 2. The erroneous data are shown as columns that extend down from the X axis. The data may be erroneous because the algorithms in the sensors are flawed, the sensors lack specificity, or the enemy has successfully spoofed the sensor network. These erroneous data flow through the model to Oval 3 (C2 workstation) and to Oval 4 (perception). The column in Oval 5 has a larger negative portion than previous columns because incorrect knowledge of doctrine or invalid experiences can distort the lens and lead to a comprehension of the situation that is only partially true. This inaccurate understanding will be the basis for a decision maker's projection (Oval 6). As a result, the column in Oval 6 may have an even larger portion of the column that extends below the X axis. It also possible that "well-focused" lenses will reduce the erroneous data or that "poorly-focused" lenses would result in a more distorted projection at Oval 6. The situations illustrated in Figures 6a and 6b are just two of many permutations showing the quantity of veridical data and erroneous data at each oval.

The analysis performed on the TNT data permitted the authors to construct a graph similar to those in Figure 6 that showed the extent to which the data flowed accurately through the DMSC. The authors reviewed the following sources of data in conducting their analysis:

- voice transcripts,
- video feed observer log,
- data compiled from the GPS tracking devices on the UAVs and enemy ground vehicles, and
- reports generated by a commercial software program that used the GPS tracking data to construct a simulation of the runs.

These data were reviewed initially to identify hits (correct identification of enemy vehicles), misses (failure to detect enemy vehicles when they were present), false alarms (identifying an entity as an enemy vehicle when none was present), and correct rejections (classifying an entity as a non-target when it is not an enemy vehicle). Four of the runs were analyzed in detail. The analysis of one of those runs is presented here.

Analysis of TNT Data

Figure 7 shows the data from an ASOM run. This particular run employed three different UAVs (Raven, Buster, and Tern). The three columns for each UAV (Techno, GCU, and TOC) indicate which agents in the system detected an entity. The Techno columns identify technological detections. The data collected from the GPS trackers and analyzed after the run indicate that a UAV and an enemy vehicle were in close proximity to one

another. The GCU columns are detections by the operators at the UAV's ground control unit. The TOC columns indicate detections by the TOC video feed observers. Detections were classified either as hits (yellow shading), misses (blue shading), false alarms (pink shading), or correct rejections (green shading). The four enemy vehicles were numbered R1 – R4.

| 1 | Time Start | Time End | Total | Raven | | | Buster | | | Tern | | |
|----|------------|----------|--------|---|-----------|-----------|--------|-----|-----|--------|----------------|-----------|
| | | | | Techno | GCU | TOC | Techno | GCU | TOC | Techno | GCU | TOC |
| 2 | 9:31:49 | | | | | | | | | | | |
| 3 | 9:32:00 | | | | | | | | | | | |
| 5 | 9:36:06 | 9:36:06 | 0.017 | R1 | | | | | | | | Visual |
| 6 | 9:37:53 | 9:37:54 | 0.637 | R1 | | | | | | | | Ver-Wh-Or |
| 7 | 9:37:53 | 9:37:54 | 0.591 | R4 | | | | | | | | |
| 8 | 9:37:57 | 9:38:01 | 4.384 | R2 | | | | | | | | |
| 9 | 9:37:57 | 9:38:00 | 3.515 | R3 | | | | | | | | |
| 10 | 9:38:10 | | | | | | | | | | | Vt |
| 11 | 9:38:28 | | | | | | | | | | | Visual |
| 12 | 9:38:29 | 9:38:29 | 0.351 | R1 | | | | | | | | |
| 13 | 9:38:29 | 9:38:29 | 0.367 | R4 | | | | | | | | |
| 14 | 9:39:10 | | | | | | | | | | | Tg |
| 15 | 9:39:15 | | | | | | | | | | | Vt |
| 16 | 9:39:25 | | | | | | | | | | | Vg |
| 17 | 9:40:00 | 9:40:01 | 0.57 | R1 | | | | | | | | |
| 18 | 9:40:00 | 9:40:01 | 0.487 | R4 | | | | | | | | |
| 19 | 9:40:07 | 9:40:09 | 2.4 | R2 | | | | | | | | |
| 20 | 9:40:07 | 9:40:09 | 2.367 | R3 | | | | | | | | |
| 21 | 9:40:27 | 9:40:35 | 8.141 | | | | R4 | | | | | |
| 22 | 9:41:46 | 9:41:53 | 7.204 | | | | R1 | | | | | |
| 23 | 9:43:45 | | | | | | | | | | | Vt |
| 24 | 9:44:21 | 9:44:22 | 1.027 | R3 | | | | | | | | |
| 25 | 9:44:42 | 9:44:42 | 0.087 | R3 | | | | | | | | |
| 26 | 9:44:43 | 9:44:43 | 0.32 | | | | R1 | | | | | |
| 27 | 9:44:43 | 9:44:47 | 4.224 | | | | R1 | | | | | |
| 28 | 9:45:17 | 9:45:21 | 4.383 | R1 | | | | | | | | |
| 29 | 9:45:31 | 9:45:43 | 11.91 | | | | R1 | X | | | | |
| 30 | 9:45:50 | | | | | | | | | | | Tt |
| 31 | 9:46:23 | 9:46:23 | 0.081 | R4 | | | | | | | | |
| 32 | 9:46:29 | 9:46:52 | 23.377 | R2 | | | | | | | | |
| 33 | 9:46:58 | 9:46:59 | 1.777 | | | | R1 | | | | | |
| 34 | 9:59:00 | | | | white SUV | white SUV | | | | | | |
| 35 | | | | | | | | | | | | |
| 36 | | | | Miss - Detected by Technology but not by GCU or TOC | | | | | | Tt | Tally Ho (TOC) | |
| 37 | | | | Hit - Detected by technology and GCU/TOC | | | | | | Vt | Visual (TOC) | |
| 38 | | | | False Alarm - Detected by TOC/GCU but not by technology | | | | | | Tg | Tally Ho (GCU) | |
| 39 | | | | Correct Rejection - No detection by Techno | | | | | | Vg | Visual (GCU) | |

Figure 7. Data from an ASOM Run that included three UAVs (Raven, Buster, and Tern)

Start times for the detections were obtained from the GPS tracking data for technological hits and from the voice transcripts for the GCU and the TOC hits. The voice transcripts did not provide data with respect to the duration of the detection. Therefore, GCU and TOC detections do not have ‘Time End’ or ‘Total’ entries. The ‘Total’ column indicates the length of time (in seconds) the enemy vehicles were within a UAV camera’s ‘footprint.’ Although the GPS tracking data were recorded once per second, one database used by the authors listed positions only every five seconds. Four other codes are present in the data:

- Vt – a visual sighting of a suspected enemy vehicle by a video feed observer in the TOC;
- Vg – a visual sighting of a suspected enemy vehicle by a GCU operator;
- Tt – a confirmed sighting of an enemy vehicle by a video feed observer in the TOC;

- Tg – a confirmed sighting of an enemy vehicle by a GCU operator.

Rows that include ‘Time Start’, ‘Time End’, and ‘Total’ entries were taken from reports generated by a commercial software program after the experiment. This software used every data point recorded (i.e., once per second) and then interpolated the data to provide exposure times for an enemy vehicle down to the millisecond.

The authors used the technological data (i.e., the data from the GPS tracking devices) as the basis for the analysis. That is, if the technological database indicated that a UAV and its camera were in a position to detect an enemy vehicle, it was considered a technological hit. The voice transcripts and the TOC video feed observer logs were then examined to determine whether the technological hit was subsequently detected by a human either at the GCU or the TOC. For example, Row 8 in Figure 7 indicates that enemy vehicle R2 was detected by the Raven UAV for 4.384 seconds from 9:39:57 to 9:38:01 but it was not detected by anyone at the GCU or in the TOC. Row 30 indicates that there was a confirmed sighting by the TOC’s Tern video feed observer but the GPS database did not show a technological hit. There also was no corresponding detection by the GCU. Therefore, the sighting by the TOC video feed observer was considered a false alarm.

In this run, there were 22 technological hits, 16 by Raven, 6 by Buster, and 0 by Tern. There appear to be six detections by humans (see rows 3-4, 10-11, 14-16, 23, 30, 34 in Figure 7), 5 by Tern and 1 by Raven. Two of these detections were confirmed sightings (rows 14 and 30). However, since the six detections by humans were not preceded with technological hits (i.e., the GPS tracking database did not indicate that a UAV and an enemy vehicle were in close proximity), the human detections had to be classified as false alarms. Figure 8 depicts the flow of data through the DMSC for this run. This figure illustrates two possible explanations for the data in Figure 7.

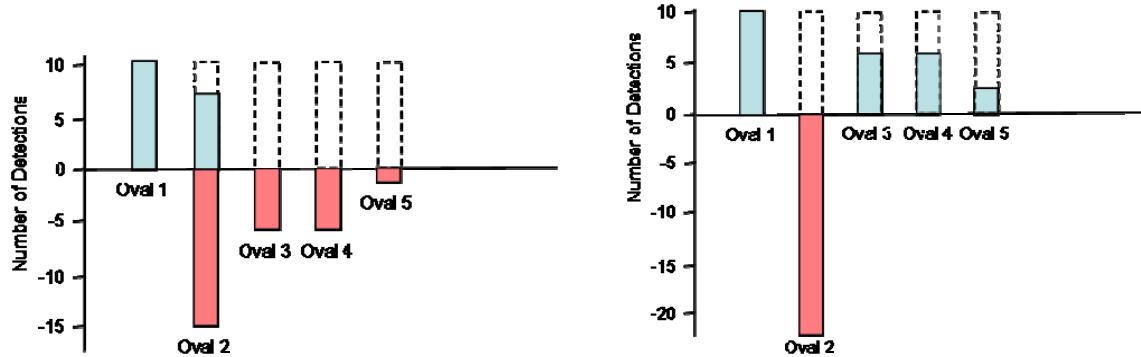


Figure 8a and 8b. Two possible flows through the DMSC.

In Figure 8a, Oval 1 depicts the number of times in which the paths of the UAVs and the enemy vehicles actually intersected. Oval 2 contains some number of actual detections (hits) and some number of erroneous detections (false alarms). The data indicate that none of the six human detections coincided with the 22 technological hits. Therefore, the six total detections and the two confirmed human detections were classified as erroneous (false alarms). Since the authors were present in the TOC and were able to detect at least

some of the enemy vehicles on the live video feed and independently confirm the locations of these vehicles with the red team commander, it seems clear that not all of the human detections were erroneous.

Figure 8b suggests an alternative flow of data through the model. Given the same number of times (approximately 10) the paths of the UAVs and the enemy vehicles intersected (Oval 1), a flawed algorithm in the technological system failed to detect any of the actual intersections but instead generated 22 erroneous technological hits. The UAV video feeds actually may have recorded six of the intersections (Oval 2), transmitted them to the GCUs and the TOC where all six were displayed (Oval 3) and perceived (Oval 4) and two were confirmed as enemy vehicles (Oval 5).

Discussion

Technology can be seductive. Data generated by sophisticated software programs and elegantly displayed on large flat panel screens give the appearance of precision and accuracy. However, on occasion, the data may be neither precise nor accurate. Such was the case with the software used to evaluate the ASOM data in this TNT exercise. The authors noticed the problems when they attempted to trace the flow of data through the DMSC. First, there was a false sense of precision. The GPS tracking data were accurate down to the second. However, the software used to generate the reports of the UAV and enemy vehicle intersections showed a level of precision down to the millisecond.

Apparently, the software interpolates the data it is given and generates reports and representations based on those interpolations. Intersections of as little as 17 milliseconds - imperceptible to a human observer - were reported.

Second, the algorithm used by the software was not properly constrained. In the scenario, all four enemy vehicles entered the battlespace through the same checkpoint at 9:21 AM. The vehicles drove to different destinations for eight minutes before the UAVs began their searches. At 9:40 AM, 19 minutes into the run, the database indicated that the Raven detected all four enemy vehicles within eight seconds (see Figure 7, rows 17 – 20). The authors did not believe this was possible, given that not all the vehicles were within the Raven's sensor footprint at that time. Subsequent discussions with the commercial software developers revealed that their product determined the 'detectability' of an enemy vehicle by reconciling the location of the UAV and the angle of its camera with the location of the enemy vehicle. Distance from the UAV to the enemy vehicle is not considered. A UAV could be 50 miles away – well beyond the ability of a human to detect a vehicle with a low quality video camera – and the software would still register it as a hit. Had the authors not attempted to trace the flow of data through the DMSC, this software anomaly may not have been uncovered. Based on the authors' findings the software developers constrained their algorithm to approximate the abilities of the human visual system.

Third, there was a lag in the transmission of the video from the UAVs to the TOC. Video data were transmitted via one network while the telemetry data that provided exact location of the UAVs was sent on another network. The telemetry data was timely, but

the video feed varied from being near real time to lagging by as much as 15 minutes. This variable lag made it difficult to reconcile the technological data with the voice transcripts and the observer logs.

Conclusion

The Dynamic Model of Situated Cognition has proven to be useful for analyzing data from computer-based simulations and for retrospective analysis of accidents. This paper explored the utility of using the model in field studies. Our conclusion is that the model is a viable framework for analyzing data from field studies such as the TNT exercises and for identifying anomalies in command and control systems. It readily identifies breakdowns as data flow through technological systems to human agents. A significant challenge to using the model in field studies is determining how to collect data efficiently in order to populate each oval of the model. Audio and video tapes often require transcription or detailed coding. GPS tracking systems generate enormous databases that must be cleaned before they can be analyzed. And, of course, the ability to collect data on red team activities is essential for determining the extent to which the friendly forces understand the battlespace. The authors plan to continue using the Dynamic Model of Situated Cognition in field studies, to refine data collection methods for the model, and to use the model to influence the design of command and control systems. Such work is imperative if all of the tenets of Network Centric Warfare are to be fully realized.

References

Alberts, David S. (1996). *Information Age Transformation: Getting to a 21st Century Military*. Washington, D.C.: DoD Command and Control Research Program.

Cebrowski, A.K. and Garstka, J.J. (January 1998). Network-centric Warfare: Its Origin and Future. *U.S. Naval Institute Proceedings*, Vol. 124/1/1,139.

Endsley, M.R. and Garland, D.J. eds., (2000) *Situation Awareness Analysis and Measurement*. Lawrence Erlbaum Associates, Mahwah, N.J.

Miller, N.L., Shattuck, L.G. (2004a). “A Process Model of Situated Cognition in Military Command and Control.” *Proceedings of the 2004 Command and Control Research and Technology Symposium*, San Diego, CA.

Miller, N.L. and Shattuck, L.G. (2004b). “A Process Tracing Approach to the Investigation of Situated Cognition.” In the *Human Factors and Ergonomics Society Annual Meeting Proceedings*. Santa Monica, CA, 658 – 662.

Miller, N.L. and Shattuck, L.G. (2005). “Applying a Dynamic Model of Situated Cognition to the Investigation of Mishaps.” In the *Human Factors and Ergonomics Society Annual Meeting Proceedings*. Santa Monica, CA, 219 - 223.

Miller, N.L. and Shattuck, L.G. (2006). "A Dynamic Process Model for the Design and Assessment of Network Centric Systems." *Proceedings of the 2006 Command and Control Research and Technology Symposium*, San Diego, CA.

Shattuck, L.G. and Miller, N.L. (2006). "Extending Naturalistic Decision Making to Complex Organizations: A Dynamic Model of Situated Cognition." *Organizational Studies*. 27(7), pp. 989 – 1009.

About the authors

Lawrence G. Shattuck is a Senior Lecturer and co-director of the Human Systems Integration Program at the Naval Postgraduate School in Monterey, California. He is a recently retired U.S. Army colonel with 30 years of service. Prior to his current position, Dr. Shattuck was a Professor of Engineering Psychology at the United States Military Academy, West Point, New York where his responsibilities included managing the Engineering Psychology Program and directing the activities of the Engineering Psychology Laboratory. His research interests include command and control, decision making, decision aiding, human error, communication of intent, and situated cognition. He holds a Ph.D. from the Ohio State University in Cognitive Systems Engineering. He can be reached at: Naval Postgraduate School, Glasgow Hall, Rm 234, Monterey, California 93943. His email address is lgshattu@nps.edu.

Nita Lewis Miller is an Associate Professor and co-director of the Humans Systems Integration Program at the Naval Postgraduate School in Monterey, California. She has faculty appointments in the Operations Research and Systems Engineering Departments where she teaches human factors engineering and human systems integration courses, directs thesis research, and pursues her research interests in individual and team performance, human fatigue in operational settings, decision-making, situation awareness and military command and control. In her work with the military, Dr. Miller has studied C4ISR, G-LOC in high performance aircraft, and the effects of fatigue and thermal stress on various aspects of human performance. Dr. Miller received her Ph.D. in Behavioral Sciences from the University of Texas School of Public Health. She can be reached at: Naval Postgraduate School, Glasgow Hall, Rm 225, Monterey, California 93943. Her email address is nlmiller@nps.edu.

Gregory A. Miller is a Lecturer in the Systems Engineering Department at the Naval Postgraduate School in Monterey, California. Mr. Miller received an M.S. in Electrical Engineering from the Naval Postgraduate School in 1992 and a B.S. in Electrical Engineering from the U.S. Naval Academy in 1987. His research interests include networked command and control and automated decision aids. His email address is gammer@nps.edu.