Visualization Techniques for Revealing Uncertainty to Decision Makers

ABSTRACT
Modern military simulations employ a variety of models to realistically represent warfighting capabilities and the environments in which these capabilities operate. However, these models rarely represent the uncertainty inherent in real-world domains, and simulations rarely depict uncertainty in decision-makers’ battlespace displays. In this paper, we describe a research program to identify and remedy deficiencies in the portrayal of uncertainty in military decision support systems. We address the issue of multiple sources of uncertainty in military systems by presenting a theoretical model of uncertainty, which builds on cutting-edge research in cognitive decision theory, human psychology, mathematics, and information systems design. We demonstrate some general strategies for visually conveying the complexity that resides within uncertain data without overly increasing the user’s cognitive workload. Our visualizations aim to incorporate the knowledge of the application domain that is necessary for the tasks so that information is provided in context, highlighting critical information, and alerting the user to the predominant aspects of uncertainty within the simulation environment. We also discuss the key quantifiable effects of this approach on human-system performance, such as reduced decision time and increased situational awareness, decision accuracy, and user confidence.

INTRODUCTION
Modern military simulation systems (e.g., Joint Semi-Automated Forces) employ a variety of models to provide realistic representations of friendly and adversarial warfighting capabilities, as well as the environments in which these capabilities are applied. These models and simulations attempt to capture the key elements needed to support training, mission rehearsal, decision support, acquisition, deployment, and tactics/strategy development. Like all models, their most important quality is their representation of the fundamental structure of a domain. Uncertainty is an aspect of the structure of almost all domains. However, these models rarely represent the uncertainty inherent in real-world domains, and simulations rarely visualize uncertainty in decision-makers’ battlespace displays.

To enable users to make better decisions when confronted with uncertainty, and to inspire users’ confidence, the models underlying a simulation system should reflect the uncertainties that are inherent in real world domains, and this uncertainty must be available for inspection by simulation users. Thus, there is a compelling need to enable modelers to represent uncertainty in a systematic, standardized manner and for simulation users to see uncertainty in the displays they use.

An analysis of the sources of uncertainty in complex, human-machine systems illustrates the variety of sources (see Figure 1), and thus the need for a comprehensive approach that addresses uncertainty in models and in displays:

- There can be uncertainty within the model itself, due to the model builder’s incomplete understanding of the real-world system being modeled, or because, in the model builder’s judgment, a real-world element need not be taken into account.

- Uncertainty can exist within the data that the model receives from the real-world. The data could be inherently variable (e.g., weather phenomena) or could, on occasion, be outside the range of a system’s sensory devices, and thus be undetectable.
• The equipment and techniques for communicating information from the system to the human observer (i.e., the user interface) may distort information, omit information, or obscure critical information in the clutter of irrelevant information.

• The human observer may misperceive patterns presented by the system due to cognitive biases. Expectancy bias, for example, leads the user to “see” what he expects to see, even when it departs from the actual signal. Information overload also promotes misperception. As information load increases people take stronger, and potentially riskier, steps to manage it, such as increasing their tolerance for error, delaying analysis, and filtering (Miller 1978, chap. 5). Thus, too much information can be just as detrimental to performance as too little (c.f., Perry and Moffat 2004).

• In a team setting, conflicting perceptions, interpretations, and responses may lead to team dysfunction or, in the best case, to unexpectedly constructive collaboration.

While there are many techniques to model and visualize uncertainty (Pang et al. 1997; Lempert 2002), uncertainty is not consistently represented in models, and it is almost never depicted into battlespace displays shown to decision-makers. In part, this is due to a lack of knowledge regarding how best to represent uncertainty within models, and how to visualize uncertainty in ways that will predictably enhance, not degrade, decision making.

The Solution

A sound solution must address the formulation of models and simulations, the design of interfaces, and the impact on decision making. In this paper, we describe the results from Phase I of an SBIR research program to identify and remedy deficiencies in the portrayal of uncertainty in military decision support systems. The goal of this SBIR research is the design and development of MUSE (Modeling Uncertainty in Shifting
Environments), a system for analyzing data, identifying sources of uncertainty within the data, and communicating that uncertainty to operators to facilitate decision making performance within the domain of the Dynamic Targeting Cell (DTC) of the Air Force Air and Space Operations Center (AOC). The key endeavors of this program were (1) formulating a comprehensive theory of uncertainty; (2) investigating techniques for visually communicating uncertainty to end users; and (3) identifying ways to factor uncertainty estimates into the decision making process.

MUSE CONCEPTS

In order to provide a context for our modeling and visualization research, we scripted a scenario involving a plausible situation in which MUSE would be used by members of a Dynamic Targeting Cell (DTC) within the Air Force Air and Space Operations Center (AOC). The DTC prosecutes targets of critical and immediate concern, and in doing so, must verify the identity and location of the target at the moment, identify suitable weapons and their availability, determine the collateral damage that will be incurred, and verify the status of the target after it has been attacked. As such, the members of the DTC must weigh a variety of factors, all of which are surrounded by uncertainty.

For our investigation, we chose three targets to be prosecuted: a moving surface-to-air missile system, a fictional leader of insurgent forces, and a WMD convoy using hostages as human shields. These were chosen to represent different levels of target priority and urgency. Further, these were chosen to demonstrate different types of uncertainty that would be faced by the DTC in making decisions regarding how to prosecute these targets. Our scenario contains a detailed account, minute-by-minute, of the events, decisions, and types of uncertainty handled by the DTC during a two and one-half hour period.

Formulating a Theory and Model of Uncertainty in Complex Systems

Our efforts for modeling uncertainty and its impacts include: (1) building a taxonomy of uncertainty and its underlying models; (2) studying how different types of uncertainty emerge during DTC operations to assess the situation and allocate weapons to targets; and (3) studying examples of DTC decisions that are influenced by different types of uncertainty. In this paper, we will describe the taxonomy of uncertainty that we developed as part of this effort.

Our flexible framework for modeling uncertainty identifies and integrates several executable models that span different types/interpretations of uncertainty. These models allow for the quantitative evaluation of uncertainty in different contexts and for the assessment of complex propagation of uncertainty effects. They provide a unified framework for evaluating uncertainty that results from multiple sources (e.g., sensor and human limitations; noise, clutter, jamming; modeling errors; algorithm limitations; data compression, interpolation and approximation; communication connectivity and bandwidth variations). Figure 1 represents this framework; the sources of uncertainty are addressed below.

TAXONOMY OF UNCERTAINTY

Our flexible framework of uncertainty builds on two cutting-edge research efforts. These are the concepts of information-based uncertainty and uncertainty-based information that are addressed by two complementary approaches – the top-down approach of the “Generalized Theory of Uncertainty” (GTU) (Zadeh 2005) and the bottom-up approach of “Generalized Information Theory” (GIT) (Klir 2005). These theories use expressive languages emerging from fuzzy set theory to generalize the information representation means (GTU) and to expand probability measures of the information theory and generalize their set-theoretic representation (GIT).

Uncertainty denotes imperfect knowledge or lack of knowledge about the world. As such, it represents the mismatch between the world and its image, i.e., the hypothesized knowledge or representation of it. Uncertainty is an inherent feature of the world and is due to the fact that the world is: (1) stochastic — so that it is hard to predict; (2) dynamic — so it is difficult to keep the knowledge of it up-to-date; and (3) ambiguous — so it is hard to interpret. In addition to the world itself, uncertainty can be attributed to the means.
Figure 2. Different models of uncertainty resulting from applications of probability theory, categorization theory, and perception theory.

for portraying its image (including the means for creating, transferring, and presenting information) and to the process of interpreting this image (including interpreting information by humans). Therefore, it is natural that uncertainty was originally studied by the three different disciplines: (1) probability theory, inspired by information theory and signal processing and resulting in probabilistic models of uncertainty (Klir 2004a, 2004b); (2) categorization theory, inspired by fuzzy logic and set theory and resulting in categorization models of uncertainty (Joslyn 1997a, 1997b); and (3) perception theory, inspired by human psychology, complexity theory, and (lately) by artificial intelligence and robotics and resulting in perception models of uncertainty (Gao 2003; Pearce, Boardman, and Ponting 2000; Dawidson 2004). Our unified framework of uncertainty links together the above three theories by integrating the corresponding baseline models from cognitive decision theory, human psychology, mathematics, and design of information systems.

Examples of different models of uncertainty are shown in Figure 2.

Our framework integrates a carefully chosen subset of the models shown in Figure 2 that enables the assessment of uncertainty relevant to the mission of the Dynamic Targeting Cell. More specifically, our framework integrates the following models for representing and quantitatively evaluating uncertainty:

1. Ontology concept maps;
2. Probability distribution and density functions;
3. Bayesian belief networks;
4. Influence networks and generalized Dynamic Bayesian networks;
5. Uncertainty spatial layout maps;
6. Markov state transition diagrams and hidden Markov models;
(7) Goal-function roadmaps (compact representations of Markov decision process graphs); and

(8) Uncertainty-driven performance-shaping mechanisms.

Our framework combines these computational models to evaluate the propagation of uncertainty effects across the DTC. These models serve as the building blocks for evaluating how complex mechanisms that result in uncertain information can be reverse-engineered to assess uncertainty, in order to improve the quality of the DTC decisions. Some of these models will be illustrated in more detail below (see the subsection entitled ‘Uncertainty at a Dynamic Targeting Cell’), where we give examples for how different types of uncertainty emerge during the process by which the DTC assesses the situation, allocates weapons to targets, and manages the execution of dynamic targets. Our framework can be generalized to incorporate any number of the uncertainty models shown in Figure 2 and include them as additional building blocks (this may be valuable when expanding our methodology to other domains, applications, and markets).

Our framework uses the corresponding uncertainty models to represent uncertainty of the three different types (Linkov et al. 2006) that arise from the sources show in Figure 1:

(i) Parameter uncertainty (attributed to sources such as measurement errors, sampling errors, systematic errors, expert judgment differences, and empirical distributions);

(ii) Model uncertainty (resulting from inaccurate model structures, incomplete representations, model misuse); and

(iii) “Modeler” uncertainty (attributed to cognitive impedance, subjective interpretation of the problem at hand, and relative influence of modeler perception on model-derived predictions).

Inferring these types of uncertainty will help devise effective strategies for reducing uncertainty, in addition to distinguishing the logical, physical, and interpretation sources of uncertainty and reverse-engineering their effects.

The challenge in evaluating uncertainty stems from the fact that (except in experimental settings) the ground truth data is inaccessible to assemble the “perfect knowledge” of the world against which to compare the available (hypothesized) knowledge and sensor data, in order to assess uncertainty in the data. Instead, techniques for evaluating uncertainty must exclusively rely on the available data and information (which is already uncertain). To devise such techniques, our framework identifies specific features of the data, information, and knowledge that imply uncertainty (and help infer it and in some cases reverse-engineer its effects to improve our knowledge of the world). These features span three different categories, such as:

(i) Data features that imply uncertainty, for example:
   - Conflict (e.g., contradictory or mutually exclusive data or opinions);
   - Nonspecificity (e.g., partial or ambiguous information that allows for alternative interpretations);
   - Small sample size or lack of observations (e.g., when some states of the model are unknown);

(ii) Model features that imply uncertainty, for example:
   - Lack of representativeness (e.g., some observation types are not represented in the model);
   - Lack of calibration (e.g., model parameters do not match observations);
   - Alternative logical implications (e.g., existence of alternative, contradictory or mutually exclusive model-based explanations of phenomena);
   - Complexity (e.g., intractability of reverse logical reasoning and implications);

(iii) “Modeler” features that imply uncertainty, for example:
   - Domain expertise mismatch (e.g., lack of hands-on experience, terminology mismatch);
• **Low trust** (e.g., mismatch between expressed belief and observation confidence statistics or hesitance to draw conclusions);

• **Bias** (e.g., strong preference for certain outcomes, predisposition to seek evidence that supports own views).

Our framework adopts several measures for different types of uncertainty, such as:

• Entropy (originally introduced to measure expected uncertainty by Shannon [1948], who showed that “gain in entropy means loss in information and vice versa”);

• Ambiguity (Klir 1993);

• Nonspecificity (introduced by Klir and Yuan [1995], generalized by Dubois and Prade [1985] for belief functions);

• Confusion (Höhle 1981);

• Dissonance (originally introduced by Yager [1983] to measure a conflict);

• Discord; Strife (Klir and Parvitz 1992);

• Vagueness; Fuzziness (Rocha 1997);

• “Information content” of a given belief (Smets 1983);

• Amount of uncertainty (AU) (Harmanec and Klir 1994).

For example, **ambiguity** represents a specific type of uncertainty and is mathematically identified with the existence of one-to-many relations, i.e., when several alternatives exist for the same question or proposition. Ambiguity can be further partitioned into the categories of **nonspecificity** (associated with unspecified alternatives) and **conflict** (associated with the existence of several alternatives with some distinctive characteristic). In the uncertainty literature, the above measures are formally defined over data sets that adhere to certain “smooth” properties that render mathematical rigor and streamline conjecture analysis. As a practical application, our framework defines simplified approximations to rapidly evaluate the corresponding generalized measures from the data that may not adhere to the above “smooth” properties.

Our framework applies decision theory, particularly in the presence of uncertainty, to devise efficient ways to use uncertainty estimates to improve the quality of decisions. Certain decisions must directly account for uncertainty (e.g., determining expected outcome under different decision strategies and courses of actions (COA); assessment of risk associated with COA; assessment of expected value to determine if a particular strategy is worth the cost and risk), while other decisions’ quality is affected by the uncertainty of the information driving the decisions. Some of the different decision strategies that humans tend to use to cope with the presence of uncertainty include:

• **“Maximax” optimistic approach** (when humans choose the alternative with the superior “best outcome”);

• **“Maximin” pessimistic approach** (when humans choose the alternative with the superior “worst outcome”);

• **Hurwicz** (when humans select the alternative with the superior “weighted average outcome” between best and worst as weighted by the decision-maker’s attitude towards risk taking);

• **Laplace insufficient reason** (when humans, if no information is available, assume that all outcomes or alternatives are equally likely, and select the alternative with the superior “expected payoff”);

• **Savage “minimax” regret** (when humans examine opportunity cost or loss, and select the one with the smallest value).

Our framework for quantitatively estimating uncertainty is directed at using these estimates to generate specific information (e.g., best/worst case outcomes, weighted average outcome, expected cost/benefit trade-off) that would enable decision-makers to reach more informed decisions. In some cases, superior decisions may utilize these additional planning points directly (e.g., the DTC operators could use the standard deviation estimates for future target location to assess the likely time of impact for hitting the target, while choosing the “worst case estimates” when assigning the asset with enough fuel to
Investigating Techniques for Visualizing Uncertainty

Within the AOC environment, the warfighter is confronted with vast amounts of information, most of which is represented as unorganized raw data. Through effective visualization techniques, however, this data can be translated into usable, actionable information (Vicente and Rasmussen 1990; Laidlaw 2001; Turner et al. 2002), allowing the operator to view functional patterns or relationships hidden within existing data and make effective decisions about the best actions to take based on those patterns. By creating and displaying the data in a more integrated form, or by visualizing information that is not readily perceptible in the environment, we can improve the real-time absorption of the information and reduce the cognitive load of the operator (Card, Mackinlay, and Schneiderman 1999).

Because of their ability to improve the perception of inaccessible information and reduce cognitive workload, visualization techniques have also been applied to the presentation of uncertainty information. Generally, uncertainty is visualized in one of two ways: (1) presenting uncertainty information as an additional piece of data, or (2) creating a visual element that encodes both the data and the associated variability (Pang, Wittenbrink, and Lodha 1997). To this end, we evaluated existing approaches that represent each of these two strategies of uncertainty visualization in both the human factors engineering and computer science fields. We then identified the existing strengths and weaknesses of these approaches, so that components of successful visualization techniques could be leveraged. Finally, we applied our cognitive visualization approach, designing a method for presenting uncertainty information while incorporating our knowledge of missions and operations within the DTC, our understanding of the warfighters’ tasks and information needs, and our comprehension of basic human visual perception, cognition, and decision-making.

TRADITIONAL APPROACHES TO UNCERTAINTY VISUALIZATION

Traditional approaches to uncertainty visualization attempt to present uncertainty caused by external, environmental variables or by imperfections in a technological system. Our review of existing methods for uncertainty visualization indicated that uncertainty caused by these sources was usually represented by altering the display of visual information through the use of different colors; by using gradation, texture, or transparency; or by altering the shape or orientation of information icons or glyphs (e.g., Andre and Cutler 1998; Gempler and Wickens 1998; Kirschenbaum and Aruda 1994; MacEachren 1992; Nunes and Kirlik 2005; Stone et al. 2006). Our review suggested that, in nearly all cases, graphical representations such as these were more successful at supporting situation awareness of uncertainty and decision making than providing numerical estimates (Andre and Culter 1998; Kirschenbaum and Aruda 1994; Stone et al. 2006).

Despite the documented success of these visualization techniques, three areas for the development of more innovative techniques were identified. First, most of the traditional approaches that we reviewed were based on the integration of several sources of uncertainty (e.g., wind speed and direction on aircraft trajectory) represented by a single visualization (e.g., predicted aircraft location presented as an area, rather than a specific location). While using an integrated representation can reduce cognitive load by saving the operator from mentally calculating overall mission uncertainty, it does not allow the operator to fully understand the factors that are contributing to this visualization, nor does it support the user in actively reducing the uncertainty to ensure mission success. As uncertainty in complex domains such as the DTC can be caused by a multitude of sources, most of which require different approaches to resolve, an effective visualization of uncertainty needs to provide a method for the user to identify the source of uncertainty to determine the course of action needed to reduce it to an acceptable level. We identified the need for this functionality
Second, most traditional approaches neglect the dimension of \textit{time} and its influence on the development of, or reduction in, uncertainty throughout a mission or task. Some research has been done examining the effectiveness of representing uncertainty linked with the prediction of future aircraft trajectories as a wedge or range of possible spatial locations (e.g., Gempler and Wickens 1998), though little benefit was found to representing uncertainty as a function of time in this manner. Apart from visualizations of this type, little work has been done to explore the visualization of uncertainty across time and no work was found to demonstrate how one might visualize the development or reduction in uncertainty over the course of a mission as a function of operator actions or external events. Understanding time constraints is essential in a time-critical environment such as the DTC, and evaluating how operator actions might increase or decrease uncertainty across time is vital to supporting situation awareness and effective decision making. To fill these gaps in current visualization techniques, we designed the MUSE visualization to represent uncertainty across mission time and to represent the influence that warfighters’ actions could have on selected sources of uncertainty.

Third, traditional visualization techniques are fairly effective at capturing uncertainty caused by environmental factors and system imperfections. In our review of the existing techniques, however, no approaches were found to address the uncertainty that might result from the actions of other humans. Within the DTC, understanding and accounting for the uncertainty associated with predicting adversarial actions and intentions is an essential task to ensuring mission success. Thus, we sought to incorporate this source of uncertainty, accounted for in the MUSE model, as a requirement for the visualization approach.

\begin{figure}[h]
\centering
\includegraphics[width=\columnwidth]{muse.png}
\caption{MUSE visualization of uncertainty timeline for a single target.}
\end{figure}

\textbf{THE MUSE APPROACH TO UNCERTAINTY VISUALIZATION}

Extending the lessons learned from our review of existing visualization techniques, we created the MUSE visualization, the basis of which is represented in Figure 3.

The MUSE visualization was designed to support the operator’s situation awareness of the degree of uncertainty associated with a specific target within the DTC, as well as the amount of time required to resolve the uncertainty to a reasonable level for target prosecution. These key parameters were shown in a timeline format, in which time to resolve (TTR) the uncertainty was represented as a function of the present mission time (shown by the blue [left] vertical line) and the time the target will no longer be pursuable (indicated by the red [right] vertical line). The optimal window of opportunity for prosecuting the target as determined by the parameters of the MUSE model also is shown on
the timeline as a shaded box. Additionally, the timeline itself represents past time as a solid line and future time as a dotted line. As mission time progresses and events develop in response to the warfighter and adversary taking actions, the time to resolve uncertainty will reflect these changes. The time to resolve the uncertainty associated with a given target is also presented as a function of source, shown by the three classes of uncertainty:

- **Environment** – e.g., populations (friendly, neutral) near target location, weather, and terrain;
- **Adversary** – e.g., their location, positive identification, potential courses of action;
- **Effects-based** – e.g., collateral damage estimate, quality of kill, risk assessment.

The MUSE visualization enables the warfighter to explore the causes and possible ways to reduce the uncertainty associated with a particular target. Figure 4 provides one example of such interaction, in which the user is presented with the option to access specific information relating to the time to resolve adversarial uncertainty (shown as icons in the grid), and the resulting imagery with a visualization of the spatial uncertainty of the adversary when the adversary location icon is selected.

**Figure 4. MUSE visualization of adversary uncertainty drill-down and exploration.**

By applying our cognitive visualization approach, we used our existing knowledge of the missions and operations within the DTC and our understanding of the warfighters’ tasks and information needs to create visualization requirements that filled gaps in existing visualization approaches. This innovative prototype of the MUSE visualization allows for the representation of uncertainty created by the adversary, as well as environmental and effects-based sources of uncertainty. By allowing the warfighter to explore the sources of uncertainty, MUSE not only supports superior situation awareness of these sources, but also provides the foundation for determining how to reduce them to acceptable, actionable levels.

To date, a Macromedia® Flash™ version of the MUSE visualization has been built and used to support heuristic evaluation and demonstration of our approach to uncertainty visualization within the context of DTC activities. We have also designed, but not yet implemented, a product-scalable system prototype capable of supporting team simulation experiments.

**Factoring Uncertainty into the Decision-Making Process**

The mission of the DTC is to find, fix, track, target, engage, and assess time-sensitive targets (TSTs). This mission is inherently difficult because the location of targets changes, and the relative priority of targets changes. TST enablers include the centralized control of all available intelligence, surveillance, and reconnaissance (ISR) assets to find the target, a streamlined decision-making process, and quick assignment of the best strike asset to destroy the target. Also inherent in dynamic targeting is risk; that is, when the process is rushed, there is heightened risk of collateral damage, fratricide, or other non-intended effects.

The dynamic targeting process often requires multiple decisions to be made at various levels and locations, and rapid coordination achieved between sensors, shooters, and decision-makers to put appropriate effects on the target. Decisions during this process aim at determining: (1) the identity, status, and time-sensitivity of the target; (2) targeting authority; (3) intended effects; (4) the cost of pursuing the target; (5) the window of opportunity (target vulnerability); (6) target-weapon pairing (i.e., the best asset to strike this target); (7) need to task additional ISR assets to provide additional information on the target; (8) the collateral damage that is likely to occur under various options; and so on. These decisions are made under time pressure and are vulnerable to uncertainty in many ways, as Table 1 illustrates. For example, because some targets are extremely...
dynamic, the definition of what is a time-sensitive target and what is not may change over time, more likely for some types of targets (e.g., a bridge that an adversarial force is moving towards in order to gain positional advantage) than for other types. As such, the value of prosecuting a given target may change over time; hence there is uncertainty as to the value of prosecuting any given target. Table 1 lists examples of how providing uncertainty estimates to DTC operators may promote the quality of DTC decisions and the quality of service for dynamic targeting.

The examples in this table represent both the information-source-perspective based types of uncertainty (i.e., parameter, model, and modeler uncertainty) and the information-user-perspective based types of uncertainty (e.g., non-specificity, conflict, confusion, etc.). The building blocks of our uncertainty framework, when architecturally joined in MUSE, will help DTC operators to literally see the uncertainty in missions they plan. This capability might, for example, enable the DTC to recognize the high uncertainty surrounding an estimate of collateral damage in a mission, and it might lead them to (a) postpone the target execution, while appropriately directing ISR sensors in theater (including observers on the ground, if available) to reduce

<table>
<thead>
<tr>
<th>Decisions</th>
<th>Information Sources</th>
<th>Uncertainty type – What may cause uncertainty (examples)</th>
<th>Benefits from knowing uncertainty</th>
</tr>
</thead>
<tbody>
<tr>
<td>Type of target</td>
<td>ISR reports, IMINT, SIGINT</td>
<td>Nonspecificity – Imagery or signal data inconclusive, highlight some features but not others</td>
<td>Focused ISR management / tasking</td>
</tr>
<tr>
<td>Location of target</td>
<td>ISR reports</td>
<td>Entropy – Several trajectories or behaviors likely for a target type</td>
<td>Superior asset utilization; improve Quality of Kill rate</td>
</tr>
<tr>
<td>Is it TST (Y/N)?</td>
<td>IMINT, SIGINT</td>
<td>Conflict – Imagery and signal data do not correlate</td>
<td>Focused ISR management / tasking</td>
</tr>
<tr>
<td>Type of TST</td>
<td>ISR reports, IMINT</td>
<td>Nonspecificity – Some target features still unknown</td>
<td>Focused ISR management / tasking</td>
</tr>
<tr>
<td>Need higher authority (Y/N)?</td>
<td>ConOps</td>
<td>Ambiguity – Target type not listed in ConOps</td>
<td>Speed up TST processing and streamline decision-making</td>
</tr>
<tr>
<td>Window of opportunity</td>
<td>All ISR in theater</td>
<td>Confusion – Target behavior inconclusive</td>
<td>Minimize wasteful asset utilization, casualties</td>
</tr>
<tr>
<td>Destroy target (Y/N)?</td>
<td>HQ; all ISR in theater</td>
<td>Vagueness – Opportunity is subject to behavior that not yet occurred</td>
<td>Minimize false alarms</td>
</tr>
<tr>
<td>Best asset to strike a target</td>
<td>Asset status reports</td>
<td>Confusion – Exact distance to target unknown</td>
<td>Friendly casualties risk reduction</td>
</tr>
<tr>
<td>Comparative value of TST vs. asset’s ATO</td>
<td>TST matrix, ATO, Cmdr Intent</td>
<td>Ambiguity – Value of target likely to change over time</td>
<td>Superior asset utilization; maximize expected mission value delivered</td>
</tr>
<tr>
<td>Task ISR for additional info (Y/N)?</td>
<td>Target folders; ISR reports</td>
<td>Ambiguity – Changes in target location and/or behavior unknown</td>
<td>Appropriate ISR tasking, Superior Quality of Service (QoS) for TST</td>
</tr>
<tr>
<td>What ISR to task with what assignment</td>
<td>Target folders</td>
<td>Nonspecificity – Exact target locations and best path across several targets of interest unknown</td>
<td>Superior ISR tasking; uncertainty reduction path planning</td>
</tr>
<tr>
<td>Likely collateral damage</td>
<td>All ISR in theater</td>
<td>Confusion – Unknown status of target neighborhood</td>
<td>Prevent “accidental” high collateral damage</td>
</tr>
</tbody>
</table>
the uncertainty or (b) use high-precision weapons to minimize collateral damage at the expense of probability of target kill and dollars.

Consider another example concerning the location of a moving target. Quantitative estimates of uncertainty of a target location at the likely time of the impact (e.g., since the target is moving very fast and may follow different trajectories) can help DTC operators calculate the “worst case” and “average” estimates of the distance an attack asset must travel and the fuel it requires (as illustrated in Figure 5). This would provide actionable information to DTC operators and help them select a superior asset package for prosecuting the target. For example, operators may use the “average” estimates to assess the most likely time of impact, while choosing the asset with enough fuel to travel the longest distance.

Figure 5. Converting uncertainty estimates into information beneficial to planning.

Our framework for quantitatively estimating uncertainty aims at converting these estimates into actionable information that the DTC operators would use to reach more informed decisions.

CONCLUSIONS

The research described herein will enable the military community to establish a deep, scientifically grounded understanding of the impact of uncertainty – in models and visual displays – on individual and team performance, and to predict the performance and evaluate the design of a generation of decision support systems that represent uncertainty. Moreover, by providing some general strategies for visually revealing the critical information that resides within uncertain data, this research is also expected to be of value in other complex, human-machine system domains where high levels of uncertainty exists, such as emergency management and air traffic control.

REFERENCES


Joslyn, C. (1997a) “Possibilistic Normalization of Inconsistent Random Intervals,” Advances in


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