Uncertainty and Automation

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ABSTRACT

There are many issues associated with the role of humans in automated systems. Among those that have received the least attention are the questions associated with uncertainty. Uncertainty is inherent in military operations, yet it is often ignored. By making assumptions, explicitly or implicitly, about the environment in which it works, automation can modify evidence of uncertainty, conceal the sources of variability, or even induce uncertainty in the user by neglecting environmental variability. This paper will explore the range of issues and suggest some ways to mitigate the effects of uncertainty associated with automation.

ASSUMPTIONS

To begin, let us consider the assumptions that underlie this paper. The reader may not agree with them. However, they are the firmly-held opinions of the author and, as such, must be made explicit for the reader to comprehend the argument herein.

The first, and most important assumption is that automation is intended to assist the human, not the other way around. It is the human who is ultimately responsible, and therefore, the human who must be in control. The automation and the human must work together to accomplish the human's goals. It follows from this assumption that in order for automation to do its part of the job, it must communicate with the user.

Second, machines are literal-minded. We have often yelled at our machines to "Do what I mean, not what I said!!!" but they can only do what we tell them to do. Humans are good at understanding intention and context. Machines are not. For example, the machine – world interface is limited to what a pre-determined subset of possible inputs. The automation might have privileged access to information that the human cannot access alone. While machines may have privileged access, they can only interpret those inputs in a pre-planned way. Surprise can not easily be accommodated.

Third, users have specific expectations about how machines will work and respond accordingly. We expect machines to work consistently, the same way every time the situation is the same. When automation works in unpredictable ways humans do know how to interpret the behavior and may not trust the information. We expect other people to differ in their behavior from time to time, but not automation. We might discount the poor performance of a co-worker who has a bad cold. Sniffling and sneezing are cues to the condition.

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Another day, the same co-worker might be especially accommodating or faster to answer a question. We can adapt to these intra-person fluctuations by observing the interpersonal signs, including direct communication. What are the cues that a machine is under (or over) performing? When automation behaves in an unexpected way, we tend to attribute it to a breakdown in functioning (hardware or software) and reject all subsequent output. As we move to adaptive automation, great care must be taken to provide cues as to the state of the system so that user and automation can continue to function as a team.

AUTOMATION

Increasing Automation (Both Military and Non-Military)

Automation increases our reach, thrust, memory, computational power, and speed. It has always been a part of work and of warfare. For example, the bow increased the range that a hunter or warrior could project his reach. With more automation even greater range is possible and the desire for increased range promotes greater and greater automation. However, the archer could usually see his target. The down side of greater range is that the throw is greater than the warrior's ability to see the target. Again, technology comes to the rescue with remote sensors. The trade-off is increased uncertainty about the target identification and location. Thus, automation is a player in both creating and mitigating the effects of the "fog of war."

Automation and Uncertainty

Automated systems now do everything from fly our airplanes to predict the weather. They use algorithms, statistical models, artificial intelligence, and other kinds of programs to perform their work. Automation does not work alone. Even at its most autonomous, it furthers the goals of humans who must directly or indirectly interact with the automation. Thus, there is (almost) always a person working with the automated systems. The question is, how much does the person know about the automation and how certain is the information received from the system? The answers to these questions are at the heart of this paper.

UNCERTAINTY

Defined

Uncertainty occurs in any situation in which the decision maker does have perfect knowledge of the true state of the world and / or the effects of contemplated actions. Causes include:

1. Observation uncertainty such as:
   - signal / sensor error
   - transmission loss or distortion
   - underrepresented information
   - data age.

2. Processing uncertainty such as:
   - statistical estimation
   - aggregation
   - smoothing
   - misapplication of assumptions
   - error propagation from previous calculations
   - rule conflicts (AI methods)

3. Reporting uncertainty such as:
   misrepresentation of uncertainty
   failure to communicate with the user
   poor format for displaying information.

Uncertainty and Automation

While, in one sense, uncertainty is in the head of the user, it is also a feature of information. Colloquially, we speak of the information being uncertain whenever it is unreliable, for any reason. Automation can mask uncertainty due to noise, unreliable measurements, missing data, etc., can amplify uncertainty with statistical or AI models inappropriately applied, and can create uncertainty in the head of the user when he or she does not know what the system is likely to do. For example, weather models use previous runs as inputs to successive runs. Thus, when a model is wrong, it propagates the errors. Despite this propagation, there is no indication of uncertainty in the model output, a very complex graphic. Figure 1 is the automatically generated output of a weather modeling / forecasting system. It is typical of many automated systems. It presents complex information in a very complex visualization and it presents all its information as if it were very precisely known. In reality, however, there are very large levels of uncertainty about much of the information in this display (exact size, orientation, location, source, etc.).

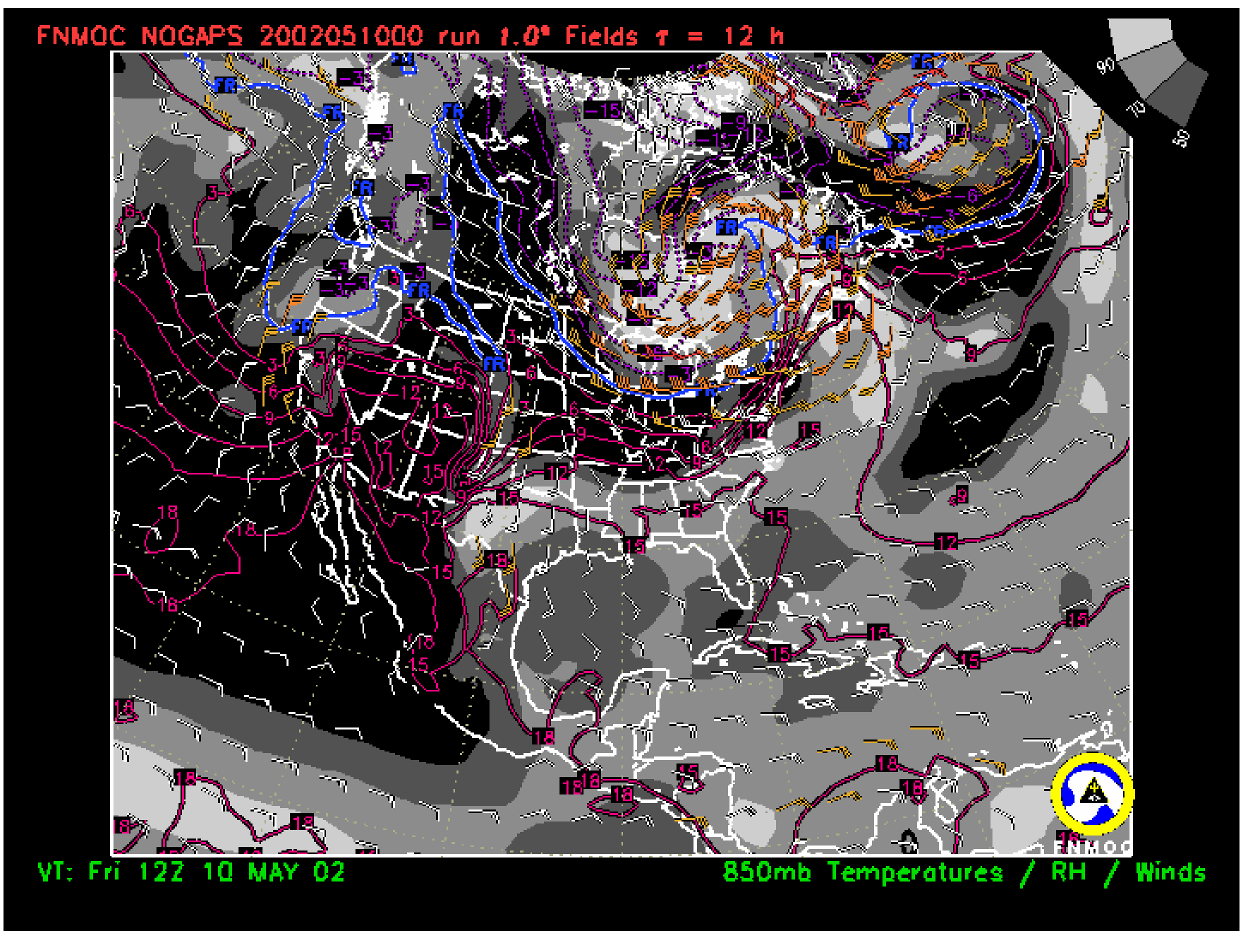

Figure 1

Uncertainty and Expertise

Experts are very aware of uncertainty. For example, the expert submariner in Figure 2 is expressing both a spatial understanding of conical angle and the associated uncertainty by gesture that includes directional hand position and dynamic motion for the degree of uncertainty. He is saying. “To me that’s always a challenge, to take the conical angle and convert it into the possible relative bearings, you know, along the cone and try to figure out what that means to me.”

Figure 2: Submarine Officer Uses Gesture that Indicates Uncertainty.

Experts are aware that there is uncertainty in most situations. They don’t simply trust the system-generated answer. For example, in an experiment with three levels of expertise, the experts showed a pattern of evaluating the reliability of automated data by checking it against “raw” data. Neither the intermediate journeymen nor the novices did this. Both were less likely to look at raw data and more likely to believe the automated information (see Figure 3).

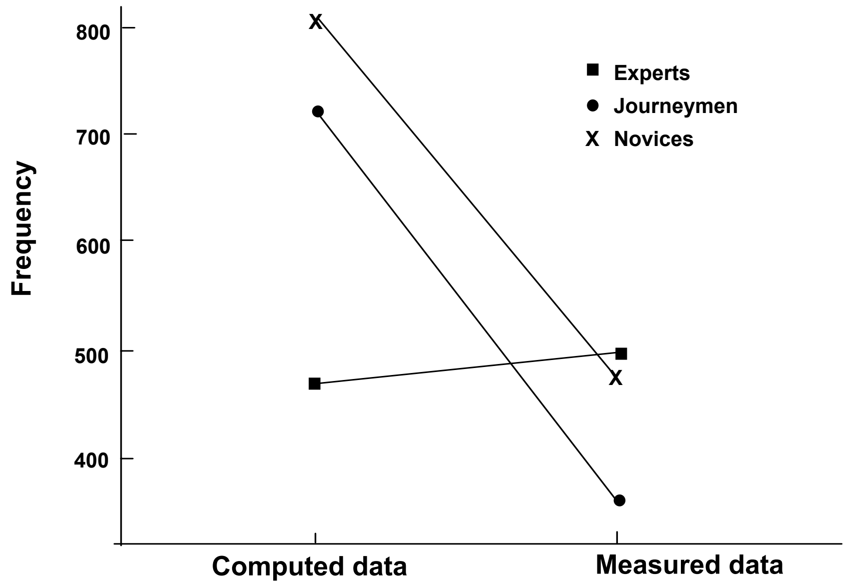

Figure 3: Experts Use Virtually Equal Amounts of Computer-Analyzed and Raw Data. Non-experts use significantly more computer-analyzed data.

In a third example, weather models system that provide no uncertainty information (see Figure 1). To evaluate how accurate the models are, weather forecasters comparing models against one another, against current conditions, and over time (see Figure 4). In this way they can evaluate the incalculable, hidden uncertainty.

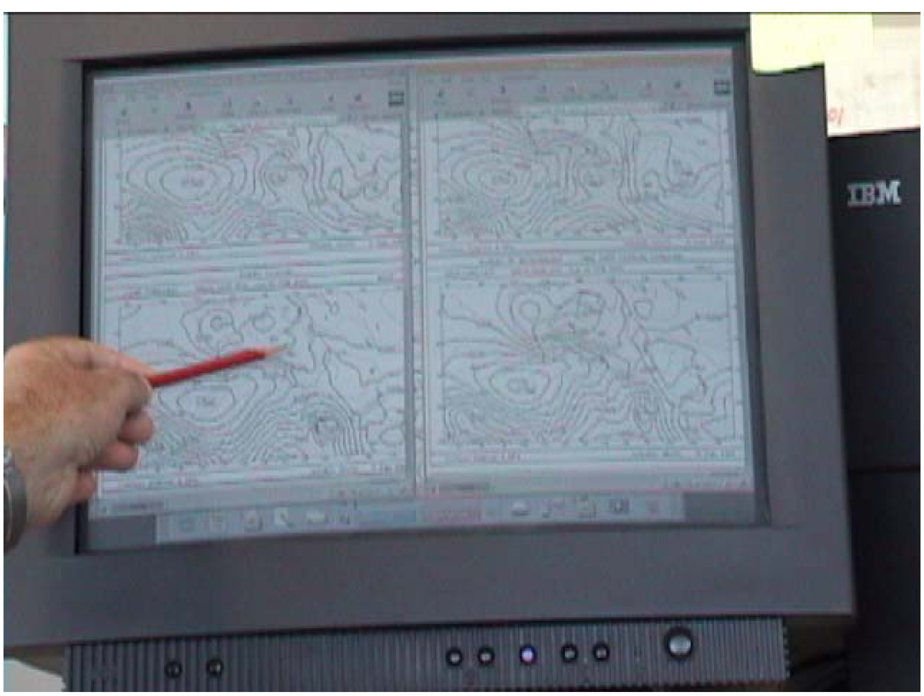

Figure 4: Weather Forecaster Comparing Predictions from Two Models.

The Representation Match Hypothesis

Knowing that experts seek to evaluate the uncertainty of automation-provided information does not provide guidance on how to display uncertainty. The representation match hypothesis provides one answer. It states that processing of uncertainty will be most effective (least errors, least time) when the representations of uncertainty match the representations required for problem solving. When there is a mismatch, additional errors or processing will occur. We propose three hypotheses that examine this issue at three different levels. The first variant hypothesizes that the match of external to internal representations is an important aspect of visualization uncertainty understanding. The more cognitive work a person has to go through to match internal to external representation (or vice versa), the more difficult the task will be.

Some Data

For example, traditionally, Target-Motion Analysis (TMA) uncertainty was displayed as a verbal descriptor. When the engineers computed a robust numerical estimate of the uncertainty around 1990, they proposed displaying it as an Area of Uncertainty (AOU) around the contact position. Kirschenbaum and Arruda [1994 #991] then tested the old verbal uncertainty against the new spatial display. Sixteen fleet experts were given simulated scenarios with two levels of difficulty (as a function of ocean noise). There were two different displays of (spatial) uncertainty: one verbal (i.e., different format) and one spatial (i.e., same format). Although there were no differences in speed across condition, there were significant differences in the range error such that the errors in the verbal condition were significantly higher than in the spatial condition, especially for high difficulty tasks (see Figure 5).

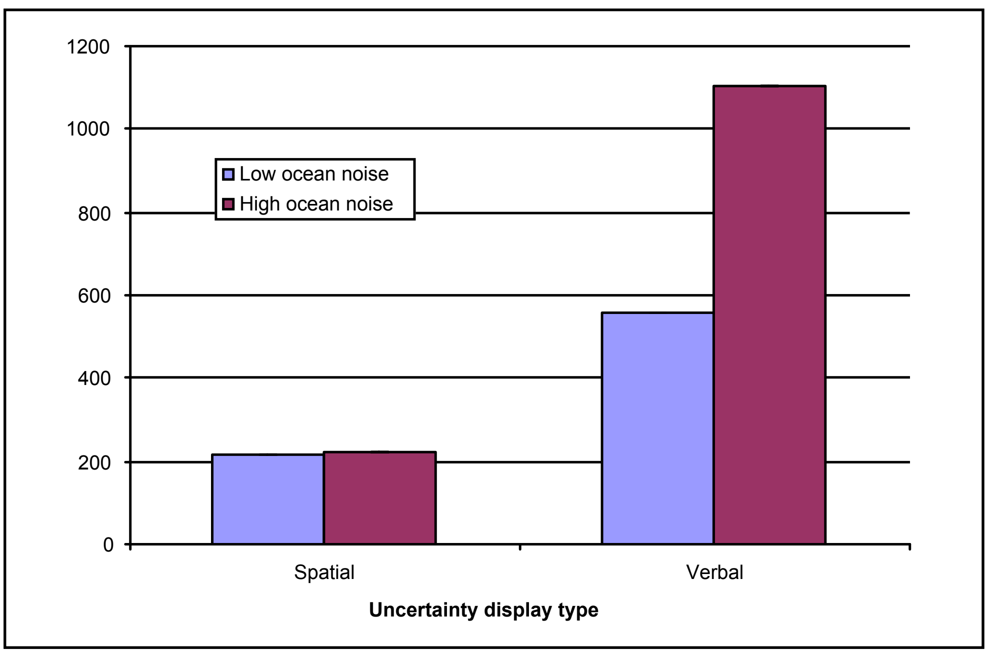

Figure 5: Range Error Noise with Verbal and Graphical Display of Uncertainty as a Function of Ocean Noise.

In ongoing research we are employing an eye-tracker to follow the user's focus of attention in a highly uncertain submarine problem. This problem employs multiple automated algorithms and displays of associated uncertainty. Figure 6 shows 10 fixations of sample data for one user from early in one scenario. Again, the expert user is assessing the uncertainty in the automation by comparing different answers and the displayed uncertainties.

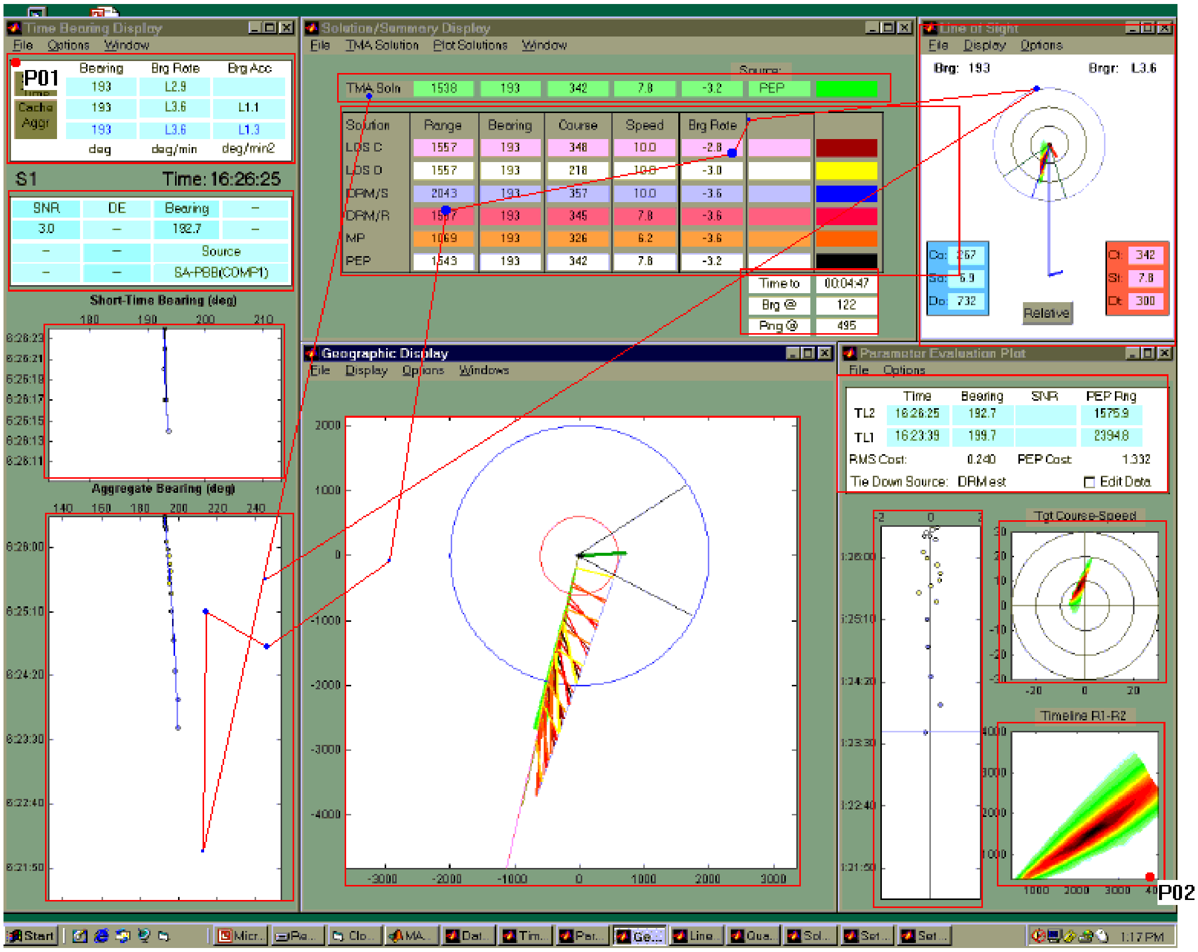

Figure 6: Ten Fixations of Sample Data for One User from Early in the Scenario. Each window displays uncertainty in a different format.

CONCLUSION

The two most important conclusions that can be drawn from this paper are that uncertainty matters and that communication between system and user is necessary, both to support user confidence and to reduce errors. Uncertainty is inherent in military operations and in the non-military world, yet it is often ignored. By making assumptions, explicitly or implicitly, about the environment in which it works, automation can modify evidence of uncertainty, conceal the sources of variability, or even induce uncertainty in the user by neglecting environmental variability. By masking that uncertainty, automation can induce human errors or delay decision making while the expert searches for confirming evidence. The Representation Match Hypothesis can guide the display of uncertainty to alleviate these problems. Finally, automation must collaborate with the user to improve the ability for both to understand the situation.

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