An External Cognition Framework for Visualizing Uncertainty in Support of Situation Awareness

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This paper discusses an approach for the development of visualizations intended to support cognitive processes deemed fundamental in the maintenance of Situation Awareness under conditions of uncertainty. We integrate ideas on external cognition from the cognitive sciences with methods for interactive visualization to help cognitive engineering examine how visualizations, and interacting with them, alter cognitive processing and decision-making. From this, we illustrate how designers and researchers can study principled variations in visualizations of uncertainty drawing from extended and enactive cognition theory.

INTRODUCTION

Nearly two decades ago, the Government Accounting Office (2001) addressed changes military organizations needed to undergo to satisfy the demands of operations in complex environments. A key challenge of a successful operational transformation rests on the ability of research and development (R&D) to improve capabilities associated with the design of decision support systems. Visualization tools supporting decision making that are not sufficiently interactive can diminish the utility of such systems. Yet, there still exists a critical gap in scientific understanding of the relationships between visualization and complex cognition. The study of visualizations and their influence on higher-order cognitive processes is relatively limited (Meyer et al., 2010). While some recommendations for the implementation of uncertainty visualization are available, the extant literature is still sparse (MacEachren et al., 2012). To contribute to this area of inquiry, we suggest that *interactive visualizations* of uncertainty need to be more thoroughly studied by cognitive engineers as a means of supporting situation awareness (SA).

SA remains an important research topic with numerous studies showing that SA is critical in complex operational contexts drawing on higher-order cognition (Patrick & Morgan, 2010; Zsambok & Klein, 1997). Additionally, models of SA have been used to inform the development of design guidelines for various systems, following the proposition that such design will enhance SA and improve performance (Durso & Sethumadhavan, 2008; Stowers et al., 2016). In this paper, we draw from Endsley's model of SA, comprised of three distinct levels: "[L1] perception of elements in the environment, [L2] comprehension of current situation, and [L3] projection of future status" (Endsley & Jones, 2011, p. 14).

An important sub-area of research is the relationship between SA and uncertainty. Within the SA literature, researchers have identified how uncertainty differentially influences various levels of SA. At L1, uncertainty is characteristic of the data collected in complex environments, often lacking completeness, credibility, reliability, congruency, temporal proximity, or interpretability. At L2, uncertainty is linked to an individual's confidence in the classification and aggregation of the data underlying their comprehension of the current situation. Uncertainty is an inherent aspect of L3, projections, and is also linked to an individual's ability to make predictions (Endsley & Jones, 2011). This brief summary forms the foundation for how we discuss visualizations in relation to SA. In the remainder of this paper, we first describe theorizing on enactive and extended cognition. From this, we illustrate how advanced methods for visualizing uncertainty can be studied. We show how principled variations in visualization can be designed such that cognitive engineering can better examine their influence on different levels of SA.

EXTENDED AND ENACTIVE COGNITION FOR SA

One way to support cognition in the face of uncertainty is through the use of externalized cognition manifest in varied representations (cf. Fiore & Wiltshire, 2016). At a general level, *representation* is concerned with how information is displayed such that it supports efficient perceptual and cognitive processing (Bisantz et al., 2011; Kirschenbaum et al., 2013; Sedig & Parsons, 2013). *Interaction* with representations adds another dimension to the manipulation of visualizations. Interaction design, in the context of representations, takes the form of determining what actions a user should be able to take to engage with the represented information. Taken together, this creates a multi-dimensional taxonomical space that can guide cognitive engineers in the study of how visualizations (both static and interactive) support decision makers. Table 1 presents a simplified factorial breakdown of how cognitive engineering research can conceptualize representation and interaction. This is illustrative of how such features can be varied with visualizations of uncertainty to study their impact on multiple forms of cognition.

Table 1. *Framework for Studying Variations in Visualizations*

		Nature of Representation	
		Static	**Dynamic**
Nature of Interaction	**Passive**	Picture or a Graph	Animation or simulation running on its own (can be a video)
	Interactive	Plug in a number and graph changes (discrete change in representation)	Full blown user control of input to see how it changes output

Each element in this framework is theoretically grounded in research from cognitive science on externalized cognition (Clark, 2001; Clark & Chalmers, 1998). In such accounts, artifacts and representations in the environment not only aid, but also constitute, a part of an individual's cognitive repertoire. One facet of this is *extended cognition* theory. Here, cognition can be viewed as distributed across the social and technical components of the environment (Fiore et al., 2010;

Hutchins, 1995). Representations in the environment serve a cognitive purpose in that what traditionally might be thought of as a cognitive process occurring within the head, is, instead offloaded or scaffolded via representations (Clark, 2008). From the cognitive sciences, "external representations are defined as knowledge and structure in the environment… and as external rules, constraints, or relations embedded in physical configurations" (Zhang, 1997, p. 180). In the present context, visualization technologies enable a vast array of external representations for cognitive engineering to study how these support complex cognition when dealing with uncertainty.

This work is also theoretically driven by the notion of *enactive cognition*. Here, there is a necessary distinction to be made between cognition merely as the processing of information, and cognition in action. In the enactive account, the environment is argued to be perceived in terms of the action possibilities that are available to an organism (Gallagher & Varga, 2014). Associated with this is the idea that an embodied and active engagement with the visualization is more likely to lead to better comprehension of information when compared to lower degrees of embodied interaction (Johnson-Glenberg et al., 2014). This drives, in part, the distinction between passive and interactive forms of representations.

We note that extended and enactive views of cognition are somewhat related to the principles of Ecological Interface Design (EID; Vicente, 2002) in that proponents emphasize the role of interaction in supporting decision-making. We similarly suggest that an interface should afford interaction with visualizations to support understanding of a situation when dealing with uncertainty. But we suggest it is the actual interaction itself that constitutes cognition; that is, it is not simply affording interaction, it is the interaction that fosters understanding of uncertainty. Furthermore, we go beyond mere affordance based theories of interaction to refine these and other potential design recommendations for SA in terms of the constructs of *enactive and extended cognition.*

Interaction as Enactive Cognition in Support of SA

Our goal is to develop a theoretical framework that integrates the aforementioned perspectives to expand research on uncertainty. What is needed is theoretically derived manipulations, and carefully controlled experimentation, to understand how to better augment cognition in the context of uncertainty. Sources of uncertainty, when viewed through the lens of the *enactive cognition* design dimensions of our framework, may provide insight to the development of new forms of human-machine interactive systems. Further, by focusing on the uncertainties attributed to the levels of SA, we offer a starting point for the application of our framework. As a starting point, we next consider a set of illustrative examples of how visualizations design guidelines might be derived from the integration of these views.

In support of SA L1, designers of visualizations may aim to make the most relevant information corresponding to data uncertainty available to the user. This data might be best represented by a static image or dynamic simulation requiring only passive interaction supporting efficient perceptual processing. A passive dynamic visualization may be best suited in environments where data is collected continuously as the visualization can allow users to perceive across time. In other environments, where data collection occurs periodically or even sporadically, the data may be best represented by a static visualization. Although it could be argued that animations are more appropriate, some caution is warranted. Specifically, animations imply temporal information that can lead a user to make erroneous assumptions about causality perceived in the visualization (Zuk & Carpendale, 2007).

As noted, active engagement with the visualization is more likely to lead to better comprehension of information when compared to lower degrees of embodied interaction (Johnson-Glenberg et al., 2014). On this basis, designers of visualizations should consider when a static or dynamic visualization with which the user can actively interact is appropriate in support of SA L2. Further, the interactions made available to the user may be multi-modal so as to provide a truly embodied interaction. For example, a user might interact with the visualization via a touchscreen, when engaged in SA L2, in such a way that the visualization truly supports the cognitive process of comprehension. In the enactive cognition view, the tight coupling between cognitive and sensorimotor processes is proposed to enable higher order cognitive processes (Goodwin, Wiltshire, Fiore, 2015). In other words, the understanding comprising SA L2 can be thought of as emerging from the brain and body's interaction with the environment such that a system facilitating interaction subsequently supports comprehension.

Interactive, dynamic visualizations may support a user's SA L3 in a manner consistent with the enactive cognition view. Much like visualizations for SA L2, designers should recognize that interactive visualizations for L3 can directly support cognitive process. Specifically, they should be developed to support users thinking through and/or seeing across possibilities. Here, our ideas coincide with the design principle of direct manipulation described in EID theory. That is, an interface should afford interaction with visualizations to support users' understanding of a situation during unanticipated events (Vicente, 2002). We suggest that interaction itself constitutes cognition and does not simply afford interaction. Interaction fosters comprehension of the uncertainty, over and above what would be possible through merely passive viewing, enabling prediction for L3.

Color Mapping as Extended Cognition in Support of SA

A key part of our theorizing is understanding the cognitive processes supported by visualizations of uncertainty. As such, we next discuss what was introduced earlier as *extended cognition* theory and how it provides a potential explanatory mechanisms for how visualizations support processes associated with SA. First, we differentiate between offloading and scaffolding (Clark, 2008; Fiore & Wiltshire, 2016) using visualizations designed to support differing cognitive processes. Then we illustrate these with the visualization technique of color mapping.

Offloading is generally the act of using the environment as a semi-permanent archive for information that can be readily available and accessed when needed, and is also used to mitigate encoding and short-term memory demands (Wilson, 2002). As such, offloading primarily serves the purpose of a memory aid that can free up cognitive resources that can then be allocated towards other processes. Scaffolding takes the form of externalizations of cognition that directly support operational processes by helping to mediate and support cognitive activity. Scaffolding, in this sense, supports more complex cognitive processing such as the analysis and interrogation of data, and, when appropriate, discussion and debate of items relevant to the task. In brief, we argue that technologically produced artifacts allow for the representation and evaluation of uncertain information. These do so by providing storage and differential access to uncertain information, thus allowing for more informed comparisons and evaluations among decision options (cf. McLoughlin & Luca, 2002).

We use color mapping as a feature of visualization that can be connected with our theorizing on extended cognition and in the context of uncertainty associated with levels of SA. Color mapping is used as an inclusive term encompassing a collection of color attributes. And there are a variety of ways to manipulate presentations of color, for example, gradient, saturation, hue, opacity, and density. Our point is that designers of visualizations can use variations of these and apply them to sources of uncertainty to support SA. For illustrative purposes, we focus on a representative form of uncertainty for each level of SA: data uncertainty in L1, confidence levels in L2, and projections in L3. Initial design recommendations can be drawn from the uncertainty types influencing SA, either offloading for L1 or scaffolding the cognitive processes of L2 and L3 in the visualization.

Offloading to support SA. Uncertainty associated with the first level of SA is designated data uncertainty. This is a general term that captures a large number of factors. For the sake of brevity, we focus on a subset to show how they can be linked to color mapping. First, consider the temporal proximity of the data. This is critical to SA in that data can be fully accurate at one point, but, due to the passage of time, the situation changes and data can become obsolete. Specifically, when data is collected at discrete time points, uncertainty emerges from the changes in the system that have occurred (i.e., data not collected continually, will not reflect temporal changes).

Visualizations of wind speeds in a region affected by a hurricane are well suited to illustrate how designers of visualization for SA can implement color mapping for uncertainty. Levels of color saturation can represent the uncertainty stemming from the timeliness of hurricane wind measurement. In a visualization of hurricane winds, the highest intensity of a color can reflect low uncertainty in timeliness of the data, meaning one is more certain in its recency. Conversely, the lowest intensity can reflect high uncertainty, meaning the data is more out-of-date. By this method, color saturation can reveal the uncertainty associated with the temporal proximity of data. Another feature of uncertainty is reliability of the data. As an example, sensor functioning can contribute to reliability. Sensors may be limited in capability or they may malfunction for many reasons. Similar to the saturation technique for timeliness, designers for SA can use visualizations representing reliability of the data with a gradient technique. Gradients can entail the use of distinct color hues or saturation levels of a single color, or both.

Uncertainty can also result from ambiguity in data. Certain environments can produce copious data such that a definitive interpretation of the data is not feasible. Opacity of a color can be used to visually represent the uncertainty resulting from ambiguous data. To demonstrate the implementation of this color attribute for designers of SA visualization, we can again consider the hurricane wind example (see Figure 1).

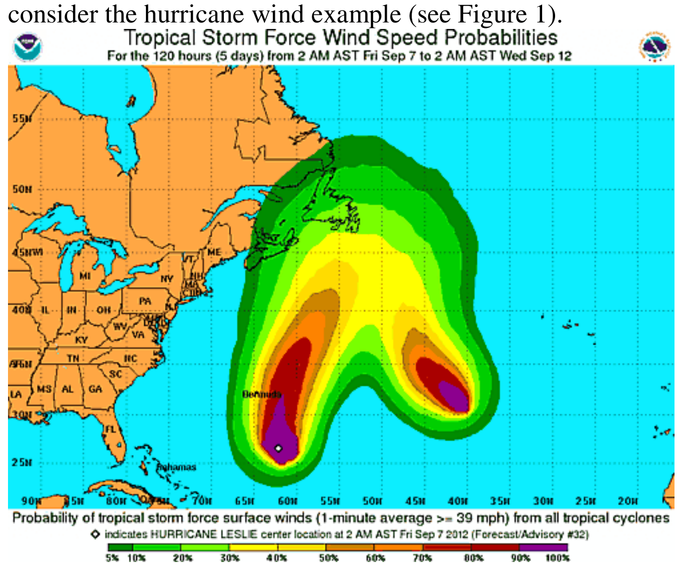

Figure 1. *Color opacity and ambiguity of data.*

The opacity of the colors used to represent numerical ranges of wind speed in such a visualization can be adjusted according to how the level of ambiguity has influenced the interpretation of existing data. It follows that higher levels of ambiguity will result in higher levels of uncertainty. In the hurricane wind visualization, a highly transparent color is indicative of high uncertainty that hurricane force winds will be found in a particular region on a map. Accordingly, a highly opaque color is indicative of low uncertainty in the likelihood of hurricane force winds in the same region of the map. The noisiness of data is another contributing factor that can produce uncertainty. The utilization of a color's granularity (i.e., coarse or fine) in visualization can represent uncertainty that arises from noisy data.

An important distinction for designers of visualizations is the relationship between levels of SA and how a system can enable progressive offloading for the decision maker. What we mean by progressive offloading is that the tool, within a level, allows the decision maker to make a set of assumptions about the data uncertainty (e.g., timeliness, reliability), and move forward with that decision externalized or offloaded into the tool. We can demonstrate this notion in considering a decision maker (DM) engaged in a course of action (COA) selection task which requires they locate a ship in a region, determine ship specifications, and how the ship is differentially affected by current and future environmental variables. For example, at L1, the DM might not know what and where for a given ship so there is uncertainty about what kind of ship it is, what it contains, and where it is exactly. The visualization would provide probabilities for each unknown and the DM will make an 'informed' decision about that ship. This decision transitions to SA L2 when the DM offloads his/her assumptions about the situation into the tool, that is, they have used the various visualizations to 'comprehend' what is going on with a ship in a given area and point in time. This offloading transition to L2 will need to be done for all elements in that decision context. The population of these coalesce to a set of COAs that the DM considers. When done, the DM will use this to transition to L3, and make predictions about future states so that a COA can be chosen. In similar ways, at L2 and L3, the DM's cognitive processes can be supported by scaffolding in the visualization.

Scaffolding to support SA. The second level of SA, comprehension, is linked to uncertainty resulting from a user's confidence levels in data categorization and aggregation methods. Confidence levels emerge from user understanding of the current system state. The categorization of data used to evaluate the state of the system can influence these confidence levels and create uncertainty. The aggregation of data can similarly influence a user's confidence, resulting in uncertainty. For the next example, we focus on confidence levels influenced by categorization capabilities of data sources. Categorization is used to describe a semantic labeling of objects in the environment. To support cognitive processes, designers of visualizations for SA can scaffold the user's comprehension and facilitate management of existing uncertainty resulting from their confidence in the categorization of pertinent data.

To illustrate, we can consider a setting in which multiple sensors are used to collect data in a region of interest, data which is then compiled for further analysis. From the aggregated data, a distinct object may be identified, or categorized, as a boat. Due to the imperfect nature of the sensors, the capability of the sensors and corresponding algorithms used to categorize an object as a boat may come into question. Thus, the user's confidence is influenced. Returning to the hurricane wind speed example, we have a visualization that includes representations of data uncertainty in SA L1. The careful integration of color mapping techniques in a visualization of hurricane wind speeds may be of use in scaffolding cognitive processes and in turn influence the user's confidence in the likelihood of a small boat being in a region affected by hurricane force winds. Designers can include the option to manipulate color attributes used for SA L1 as it is a potentially powerful means of supporting L2. In line with enactive cognition theory, adjusting the visualization, to reflect alternative possible environmental conditions, can aid the user in understanding the contingencies affecting the current state. From this, the user can develop appropriate levels of confidence in comprehension.

Uncertainty is inherent in the third level of SA. As L3 is concerned with making a decision about what to do next based upon predictions about future states, a visualization designed to simulate future states may scaffold decision making and support SA L3. Visualization can be used to aid this process by varying the size dimension of a COA tool. Here, after a DM has addressed SA L1 and L2, where they have dealt with the various forms of uncertainty around data, they can make comparisons across COAs. In earlier phases, the user has drilled down on different spaces within some environment. Now, the visualization can expand their perspective and see those options in parallel. With this, the enriched comprehension (i.e., greater detail of understanding afforded by the granular visualization), is now used for comparative purposes. In this way, a potentially superior COA can be chosen.

The exact means by which the color mapping techniques might best scaffold cognitive processes in SA L2 and L3 remains an open question. However, our framework can help illuminate the possibilities available for scaffolding cognitive processes in visualizations. In the final section, we illustrate how a complex visualization – dynamic and interactive – provides a foundation for varying color mapping and additional features that can be adapted in service of research on SA.

Dynamic and interactive visualizations to support SA. To illustrate a portion of the dimensions of our framework, we next examine a scientific visualization that is interactive and dynamic and implements color mapping techniques. The scientific visualization example we discuss in this section was developed by visualization researchers at Brown University as part of a larger initiative on the development of the Brown Widget Library (LaViola et al., 2009).

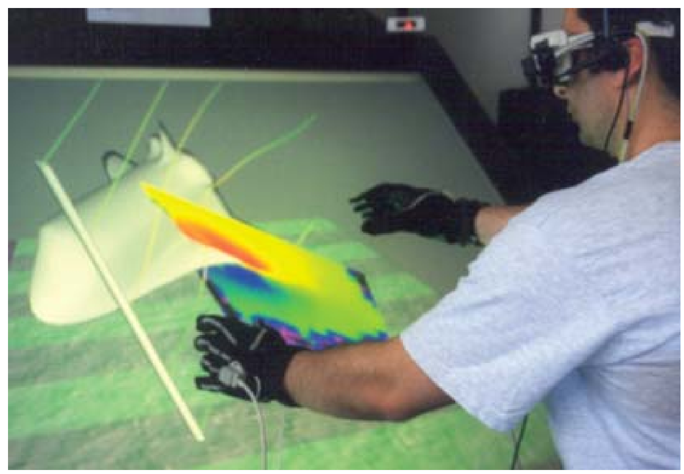

Figure 2. *User interacting with a dataset in IVR-based interactive visualization system.*

LaViola and colleagues (2009) constructed a dynamic scientific visualization for scientists to interactively visualize air flow data around a space shuttle (Figure 2). While this visualization was not designed to represent uncertainty, their use of color plane techniques illustrate how visualizations can serve to offload information and scaffold cognitive processes. Color planes are interactive tools that let users see data by presenting a plane that can be moved through a 3D space showing a color mapped representation of data within a given dataset. As such, a color plane allows features of the problem environment to be exploited to support comprehension. For example, a color plane could be used to see the different velocities in a fluid flow simulation that represent air flowing past an airplane wing at a particular location. In such a case, the color plane could map different shades of green to lower flow velocities and different shades of red to higher velocities. The color plane itself is a general visualization primitive in that it can visualize a variety of different types of data using many different color schemes. Different shades of the same color, different colors, or a combination of the two could be used to map data in the color plane. Color planes can also be resized so the plane could show a large region of data or a small area of focus. In addition, different resolutions can be employed in the color plane. Higher resolutions can present greater detail while lower provide a coarse representation of the visualized data.

Regardless of color mapping used, color planes have the following key characteristics that make them ideal for studying uncertainty: (1) they are interactive; (2), they can be moved in 2D or 3D space; and, (3) they present information to the user dynamically (i.e., as the user moves the plane, the visualization updates in real time). This particular visualization supports several modes of interaction via its multimodal interface situated in an immersive VR. The color plane tool grants the user the ability to manipulate, or interact with, various attributes to learn more detail about the visualization. This visualization is dynamic because it shows change and it is interactive because the user has the option to choose the components of the visualization on which they want to focus. With this brief illustration, we can see how the features it enables represent important opportunities for R&D on uncertainty visualizations supporting differing levels of SA.

CONCLUSION

Uncertainty plays a large role in influencing individual decision-making and the underlying cognitive processes in human-machine interactive systems. Visualizations can serve to mitigate the deleterious effects resulting from uncertainty and loss of SA. We suggest that new visualization types characterized by varying representations and degrees of interaction can support complex cognitive processes in human-machine interactive systems. We drew from external cognition theory and described enactive cognition and its role in complex cognitive processes. We elaborated on the ways visualization researchers can draw from extended cognition to augment designs to better offload information uncertainty and scaffold the cognitive processes of SA affected by uncertainty. From this, we have described how advanced methods for visualizing uncertainty can be studied. We expanded on design recommendations proposed to support SA through an integration of computer science with theorizing in the cognitive sciences.

In sum, we demonstrate how the constructs of extended and enactive cognition can inform the development of principled variations in visualization to specifically examine their influence on different levels of SA. From this, we move cognitive engineering closer to the realization of developing truly hybrid human-machine teams.

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