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<tr>
<td>10D SART</td>
<td>10-Dimensional Situational Awareness Rating Technique</td>
</tr>
<tr>
<td>CBRNE</td>
<td>Chemical, Biological, Radiological, Nuclear, and Explosive</td>
</tr>
<tr>
<td>CbTA</td>
<td>Constraint-based Task Analysis</td>
</tr>
<tr>
<td>CIFA</td>
<td>Cognitive Information Flow Analysis</td>
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<td>CTA</td>
<td>Cognitive Task Analysis</td>
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<td>CWA</td>
<td>Cognitive Work Analysis</td>
</tr>
<tr>
<td>DIARE</td>
<td>Decision Information Abstracted to a Relevant Encapsulation</td>
</tr>
<tr>
<td>EMS</td>
<td>Emergency Medical Services</td>
</tr>
<tr>
<td>EOC</td>
<td>Emergency Operation Center</td>
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<td>ES(d)</td>
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<tr>
<td>GOMS</td>
<td>Goals, Operators, Methods, and Selection rules</td>
</tr>
<tr>
<td>GVA</td>
<td>General Visualization Abstraction</td>
</tr>
<tr>
<td>HAZMat</td>
<td>Hazardous Material</td>
</tr>
<tr>
<td>HRI</td>
<td>Human Robot Interface</td>
</tr>
<tr>
<td>HTA</td>
<td>Hierarchical Task Analysis</td>
</tr>
<tr>
<td>IC</td>
<td>Incident Center</td>
</tr>
<tr>
<td>MO</td>
<td>Many at a time and Optional</td>
</tr>
<tr>
<td>MR</td>
<td>Many at a time and Required</td>
</tr>
<tr>
<td>MRQ</td>
<td>Multiple Resources Questionnaire</td>
</tr>
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<td>OEM</td>
<td>Office of Emergency Management</td>
</tr>
<tr>
<td>Abbreviation</td>
<td>Description</td>
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<tr>
<td>OO</td>
<td>One at a time and Optional</td>
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<tr>
<td>OR</td>
<td>One at a time and Required</td>
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<td>SA</td>
<td>Situational Awareness</td>
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<td>Situation Awareness Global Assessment Technique</td>
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<td>SD</td>
<td>Standard Deviation</td>
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<td>US&amp;R</td>
<td>Urban Search and Rescue</td>
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<td>USA</td>
<td>United States of America</td>
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<td>UV</td>
<td>Unmanned Vehicle</td>
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CHAPTER I

INTRODUCTION

The proposed work seeks to inform the development of a system of human-robot interfaces where each interface permits information sharing and visualization at the appropriate abstraction level given users’ responsibilities and position in a hierarchical command structure. This proposal presents the results of two cognitive tasks analyses (CTA) and the integration of the CTA results into the newly proposed Cognitive Information Flow Analysis. These results are the basis for the proposed system of interface visualizations. The primary contribution of this dissertation will be the development and evaluation of two visualization techniques, i.e. the General Visualization Abstraction (GVA) algorithm and the Decision Information Abstracted to a Relevant Encapsulation (DIARE) objects, which provide integration, abstraction, and sharing of the information generated by the remotely deployed robots.

The response to emergency incidents, including Chemical, Biological, Radiological, Nuclear, and Explosive (CBRNE) incidents (a.k.a. weapons of mass destruction) are slowly evolving from a response involving humans with equipment to a response system combining humans and incorporating information technology. The response to CBRNE incidents, including all response components (i.e. humans, equipment, and thinking machines) is collectively referred to as the CBRNE response system. The difference between equipment (e.g. fire engines, radios, maps) and thinking machines (e.g. robots, computerized decision support systems) is that machines
incorporate some cognitive abilities. If the CBRNE response system is to take effective advantage of emerging technology, the response activity needs to be understood in a way that facilitates the incorporation of these thinking machines and the development of effective human machine interactions. The incorporation of new thinking machines into the CBRNE response system is resulting in a shift, abet slowly, to a new paradigm.

One method of reaching this new paradigm is to infuse CBRNE incidents with robots that assist with dangerous tasks and extend the life saving resources available to the responders. Several researchers have studied employing or developing robots (i.e., unmanned aerial and ground vehicles) for emergency response which includes: urban search and rescue (Murphy, 2004; Wegner & Anderson, 2006; Baker, Casey, Keyes, & Yanco, 2004; Yokokohji, Tubouchi, Tanaka, Yoshida, Koyanagi, Matsuno, et al., 2006; Burke, Murphy, Coovert, & Riddle, 2004), natural disasters (Murphy, Steimle, Griffin, Cullins, Hall, & Pratt, 2008; Murphy & Stover, 2008), emergency incidences (H. Jones & Hinds, 2002; Lundberg, Christensen, & Hedstrom, 2005; Amano, 2002; Lundberg, 2007), CBRNE (Adams, 2005; Humphrey & Adams, 2008), and wilderness search and rescue (Goodrich, Cooper, Adams, Humphrey, Zeeman, & Buss, 2007; Goodrich, Bryan S. Morse, Gerhardt, Cooper, Quigley, Adams, et al., 2008).

The new CBRNE response system that employs robotic technology is considered a semi-revolutionary system. A semi-revolutionary system is similar to a revolutionary system, which is defined as a new system with no existing organizational structure, users, hardware, software, or interface methods (Cummings, 2003; Vicente, 1999). A semi-revolutionary system differs from a revolutionary system in that only some of the hardware, software, interaction methods, organization structure, and users do not exist. In
other words, the new system extends or alters portions of the original system, but does not replace the entire original system or represent an entirely new system. The CBRNE response system resulting from the introduction of robotic technologies and visualization methods developed by this research is considered a semi-revolutionary system.

Conducting a Cognitive Task Analysis (CTA) has been shown to assist with developing and introducing new robotic technology by facilitating an understanding of the domain and robot appropriate tasks (Adams, 2005; Almirao, da Silva, Scott, & Cummings, 2007; Goodrich et al., 2008; Adams, Humphrey, Goodrich, Cooper, Bryan S. Morse, Engh, et al., 2008). Although CTA methods have been conducted for a large number of domains (Endsley, Bolté, & D. G. Jones, 2003; Shepherd, 2000; Vicente, 1999; Yates, 2007), the CBRNE response system presents additional challenges because it is a human based system and involves a significantly broader scope than most systems evaluated with CTA. Most systems analyzed by a CTA technique have one or a few operators using a physical system (e.g. chemical plant). The current CBRNE response system, in contrast, has many “operators” or decision-makers at many different leadership levels and responsibilities. The system is a collection of humans, including decision-makers at various hierarchical levels, and their equipment. The scale of the CBRNE response system can be very large both in terms of geographic dispersion and in terms of the number of people involved in the response system. Considering these challenges, two CTA techniques were chosen: Goal-Directed Task Analysis (GDTA) (Endsley et al., 2003) and Cognitive Work Analysis (CWA) (Vicente, 1999). Furthermore, this dissertation represents the first application of these methods for
modeling humans as system components instead of system operators and serves as the basis for all subsequent research in this dissertation.

The Cognitive Information Flow Analysis (CIFA) was developed and applied to the CTA results in order to provide a bridge between the analyses and the design and development of the proposed system of human-robot interfaces. The CIFA focuses on the path of information as it is passes through and is transformed by the system at the different user levels, where user levels are defined as classes of humans who interact with the proposed robotic system. The CIFA results form part of the basis for the proposed interface visualizations.

There are two purposes in analyzing the CBRNE response system. The first is to understand how the current CBRNE response system operates. The second purpose is to inform the design and implementation of new robotic technology and determine how that new technology will integrate and alter the current system. The first purpose is accomplished by conducting the two CTA techniques: GDTA and CWA. The second purpose has two components: understanding how to inform the design and integrate with the current system, and the implementation of new robotic technology. Informing the system design is accomplished by using the results from the GDTA, CWA, and the CIFA techniques. The implementation of the technology requires developing the robotic hardware and the corresponding human-robot interaction and visualization techniques that allow humans to command, control, and use the resulting robotic derived information (e.g. sensor reading and images).
These proposed CBRNE response system robotic technologies will use computer-based visualizations for both command and control of the robots, and for providing feedback from the robots. This dissertation will focus on exploring two new visualization concepts. The first concept is the General Visualization Abstraction (GVA) algorithm that will appropriately display the most useful information at any given time. The GVA algorithm will employ two primary techniques to abstract the information: filtering and clustering. The second visualization concept, Decision Information Abstracted to a Relevant Encapsulation (DIARE) objects, is designed to facilitate sharing decision-relevant information for particular moments in time with other system users.

In summary, the contributions of this work are as follows. The first contribution is the cognitive task analyses (i.e., the GDTA and CWA techniques) of the human-centric CBRNE response system for the use of incorporating robotic technology. The second contribution is the addition of the extensions to the GDTA and CWA techniques to accommodate a human based system as well as the CBRNE response system scope. The third contribution is the introduction of the CIFA technique to provide a bridge between the GDTA and CWA results and a system implementation. The fourth contribution is the formation of the human-robotic interaction levels for a CBRNE response system, which includes the addition of one new user level beyond Goodrich and Schultz (2007). The fifth contribution is methods that transform the CIFA results into human-robot interaction visualizations. The sixth contribution is the GVA algorithm framework and the corresponding algorithm implementation and validation. The seventh contribution is the DIARE object concept and the concept’s implementation and validation. The final
contribution is the implementation and user system evaluation (i.e. robots and visualizations) for use in CBRNE incidents.

The remainder of this proposal is arranged as follows. Chapter II provides a literature review, including review of several CTA techniques and a review of visualization techniques related to the GVA algorithm and DIARE concepts. Chapter III presents the methodology and results from the GDTA and CWA techniques. Chapter IV presents the human-robotic user interaction levels. Chapter V presents the CIFA technique including how it compares to GDTA and CWA, and the associated results from the CBRNE response system. Chapter VI presents the GVA algorithm and the DIARE visualization concepts. Chapter VII presents the pilot results of the proposed robotic system to be used in CBRNE incidences. Chapter VIII presents the design of experiments for the user system evaluation. Chapter IX presents the proposed timeline, the deliverables, and summarizes the contributions of this work.
CHAPTER II

LITERATURE REVIEW

The CBRNE Response System

This dissertation is designed to apply to the Chemical, Biological, Radiological, Nuclear, and Explosive (CBRNE), a.k.a. weapons of mass destruction, response system. The CBRNE response system is the collection of humans (e.g. responders, government officials, civilians), equipment (e.g. protective suits, vehicles, sensors), and, in the future, computing machines (e.g. decision support systems, robotics) that function as a system to respond to CBRNE incidents. The main difference between general emergency incidents (e.g. fires, hurricanes) and CBRNE incidents is that CBRNE incidents involve serious hazards (e.g. they require protective equipment) and are often deliberate acts with the intention to kill, sicken, and disrupt society (“CBRN,” 2008). CBRNE incidents are often acts of asymmetric warfare by terrorist(s) on a civilian population, although occasionally CBRNE incidents are a result of accidents. The CBRNE term denotes the five major hazard types employed in these incidents: chemical, biological, radiological, nuclear, and explosive. CBRNE incidents can range in scale from those that affect a few people in a neighborhood or building, to those that affect millions of people in large regions. CBRNE incidents are infrequent, but have a very long history dating back to at least 1886 in the United States of America (USA) (“List of terrorist incidents,” 2008).
The earliest listed CBRNE incident in the USA was Haymarket affair, which turned a rally on May 4th 1886 in Chicago into a riot/massacre because someone threw a bomb at the police (“Haymarket affair,” 2008; “List of terrorist incidents,” 2008). Other recent notable CBRNE incidents in the USA were: the 1984 Rajneeshee bioterror attack (“1984 Rajneeshee bioterror attack,” 2008), the 1993 World Trade Center bombing (“1993 World Trade Center bombing,” 2008), the 1995 Oklahoma City bombing (“Oklahoma City bombing,” 2008), the 2001 September 11 attacks (“September 11, 2001 attacks,” 2008), and the 2001 Anthrax attacks (“2001 anthrax attacks,” 2008). There are many more CBRNE incidents that have occurred both within and outside the USA or that have been thwarted (“List of terrorist incidents,” 2008). Most of the CBRNE incidents, to-date, have employed explosive hazards (i.e. bombs); however, the potential reach of other hazards is far greater with generally longer lasting health affects making the need to effectively respond to CBRNE incidents of great importance. Furthermore, every CBRNE incident is different, often dramatically, in part because of different hazards, locations, circumstances, and responding resources. One of the purposes of this work is to facilitate the incorporation of robotic technologies into the CBRNE response system in order to provide more efficient achievement of the three overarching CBRNE response goals.

The *three overarching goals* of any CBRNE incident are life safety, incident stabilization, and property conservation (Shane, 2005). Life safety focuses on minimizing the risk to the responders, ensuring individuals not currently affected by the incident remain safe, and saving as many victim lives as possible. Incident stabilization is the process of containing and mitigating the hazards causing the incident. Property
conservation preserves or protects both physical property (e.g. buildings, trees) and commerce (e.g. shipping traffic, customer traffic).

The premise behind incorporating robotic technologies into the CBRNE response system is that the use of robots will improve the life safety goal by extending the range of responders thereby allowing them to remain safer while possibly locating hazards and victims sooner. The use of robots can improve the incident stabilization goal by providing better diagnostics and monitoring of the situation; thereby, allowing the responder to make more informed decisions that can lead to better or quicker incident stabilization. The third overarching goal, property conservation, can be improved because by utilizing the robots to improving the first two goals facilitate a quicker response thereby reducing the hazard’s duration and lingering impact on property and commerce. The incorporation of robotic technologies should not be haphazard, but be the result of a deliberate analysis (Adams, 2002). This analysis should aim to understand the CBRNE response system both as it is now without robots and as it may be with robots. The type of analysis performed on the CBRNE response system is called Cognitive Task Analysis.

Cognitive Task Analysis Techniques Review

Cognitive Task Analysis (CTA) techniques are designed to elicit knowledge that captures the unobservable cognitive processes, decisions, and judgments that compose expert performance in a system (Yates, 2007). CTA techniques structure this elicited knowledge into models and the differences between these models is what comprises the different CTA techniques. These techniques are particularly appropriate for analyzing the
CBRNE response system because the knowledge captured by CTA techniques (i.e. cognitive processes, decisions, and judgments) is what will be affected by the introduction of new robotic technology and understanding these affects are important for successful integration of the new robotic technology.

A CTA used for modeling the CBRNE response system must be able to express the interconnectivity of the various CBRNE response system components; express partial orderings of these components; and serve as a guide to developing the resulting command and control of the humans and robots system. There are many CTA techniques (Yates, 2007); however, only the CTA techniques used for systems similar to the CBRNE response system (i.e., complex human machine system, will be discussed.)

The concept of Situational Awareness (SA) has been shown to be important in developing human-robotic interaction, especially remote robots, and therefore be represented in the CTA used for the CBRNE response system (Drury, Scholtz, & Yanco, 2003; Scholtz, Antonishek, & Young, 2005; Yanco & Drury, 2004). SA is defined as “the perception of elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future” (Endsley, 1988, 1995a; Endsley et al., 2003). The capturing of SA is particularly important for the CBRNE response system because a large percentage of the response system requires perception and comprehension of the environment and its hazards and the projection of hazards effects into the near future, which map to components of SA (i.e. perception, comprehension, and projection) (Shane, 2005). Therefore, the discussion of the CTA techniques will include how a particular technique does or does not support SA.
Categorizing CTA techniques

The CTA techniques reviewed in this chapter are divided into three categories according to a basic taxonomy. The taxonomy separates the CTA techniques according to their basic modeling focus, that is, whether the technique primarily focuses on modeling goals or modeling information or data. A CTA technique focused on goals and sub-goals will henceforth be referred to as a *goal-driven cognitive task analysis*, or goal-driven CTA. The second category focuses on the path or flow of the information or data, and henceforth will be referred to as an *information-driven cognitive task analysis*, or information-driven CTA. The third category of CTA techniques is one that combines elements from both the goal-driven and information-driven groups, and is henceforth called *crossover cognitive task analysis*, or crossover CTA. This taxonomy is based on the descriptions and the theoretical framework behind the reviewed CTA techniques and, therefore, is not reclassifying the CTA techniques but is instead designed to add clarity to the presentation of this chapter since a well-established classification system for CTA techniques does not exist (Yates, 2007).

A goal-driven CTA technique is designed to model the overall task by identifying the task goals and then subsequently the sub-goals and subtasks that comprise the parent goal or task. This relationship between goals and sub-goals and between task and subtasks is called a *part-whole* relationship (Shepherd, 1998, 2000; Vicente, 1999). An analogy for a part-whole relationship is a car: the car is the whole, which is comprised of parts, such as tires. Some goal-driven CTA techniques may have other types of
relationships in addition to this relationship, but a part-whole relationship is always present in goal-driven CTA techniques. The information, or data, required to complete a function or goal is not explicitly represented in a goal-driven CTA technique.

An information-driven CTA technique is designed to model a path or paths in which information or knowledge is directed to achieve the overall task. Subtasks can be represented in an information-driven CTA technique, but only in terms of how the functions consume, alter, or create information. Therefore, the relationship between the tasks in an information-driven CTA technique is a consumer-producer relationship (Johnston, Hanna, & Millar, 2004). An analogy for a consumer-producer relationship is that in order to write a review paper one must “consume” or read many other papers, which are the products of other writers. The reasons tasks are executed are not explicitly represented in an information-driven CTA technique.

A crossover CTA technique is one that is either primarily a goal-driven or information-driven CTA technique, which crosses over and represents elements from the other task analysis category. For example, a goal-driven CTA technique that explicitly represents information required by each goal and sub-goals is considered a crossover CTA technique.

**Cognitive Work Analysis Decomposed**

Before presenting the CTA categorization, it is necessary to first present an overview of Cognitive Work Analysis (CWA), as CWA is not a single method but a collection of methods. According to Vicente (1999), Cognitive Work Analysis is a
framework for analyzing human work based on device-independent constraints and contains models of the system independent of any particular worker, control tasks, cognitive task procedures, social-organizational factors, and worker competencies. The purpose of CWA is to assist designers of computer-based information support systems in understanding the socio-technical context in which the workers perform ordinary or unexpected jobs (Vicente, 1999). This section discussing the methods that comprise CWA and how CWA and its methods relate to the three categories of CTA: Goal-driven, Information-driven and Crossover.

Cognitive Work Analysis Methods

Traditional CWA consists of five separate stages: Work Domain Analysis (WDA), Constraint-based Task Analysis (CbTA), analysis of effective strategies, analysis of social and organizational factors, and identification of demands on worker competencies (Vicente, 1999). CWA begins by understanding the environment in which the system is used. As the environment is understood, the analysis transitions its focus from ecological elements to a cognitive analysis to account for the user’s actions. Traditional CWA assumes that the system exists and only the human system interaction is being redesigned. However, the CBRNE response system with robotic technology is a semi-revolutionary system, a new system that extends or alters components of original system, but does not replace the entire original system or represent an entirely new system. CWA was extended to revolutionary domains by Cummings (2003) with the introduction of two additional steps: analysis of global social, organizational, and ethical
factors, and the creation of a simulated domain. The semi-revolutionary CBRNE response system is more similar to revolutionary systems than evolutionary systems. Therefore, modified CWA is believed to be applicable and was used to analyze the CBRNE response system.

Although CWA was initially created for modeling causal systems such as process control plants, it has since been adapted to model various intentional and revolutionary systems. Systems analyzed by CWA that are similar to the CBRNE response system include those in military (Cummings & Guerlain, 2003; Cummings, 2003; Naikar, Pearce, Drumm, & Sanderson, 2003), emergency management (Vicente, 1999), and wilderness search and rescue domains (Adams, Cooper, Goodrich, Humphrey, Quiqley, Buss, et al., 2007; Adams et al., 2008). CWA and modified CWA are constraint-based approaches that are intended to provide an overarching framework that yields information and insight even in unanticipated scenarios.

There are seven methods that comprise modified CWA as depicted in Figure 1 and they are: analysis of global social, organizational, and ethical factors; Work Domain Analysis; Constraint-based Task Analysis; creation of a Simulated Domain; Analysis of Effective Strategies; Analysis of Social and Organizational Factors; and identifying demands on Worker Competencies (Cummings, 2003).
The analysis of global social, organizational, and ethical factors is designed to foster safer, more effective development of novel technology (Cummings, 2003). The analysis increases the designer’s development of a “moral imagination” and an ethical mental model as the system has the ability to affect the welfare and safety of the public (Gorman, Mehalik, & Werhane, 1999). This analysis has three elements: Relevant Social Groups, Communication Flow Map, and Ethical Factors.

Relevant Social Groups identifies stakeholders, those individuals and groups that either influence or are influenced by the system being analyzed (Cummings, 2003). The Communication Flow Map is designed to illustrate how the different social groups communicate with each other and consequently how information is passed between these
groups (Cummings, 2003). A Communication Flow Map example, from Cummings (2003), is presented in Figure 2. The Ethical Factors element of the modified CWA is to identify and address possible ethical issues that can arise both in the construction and in the use of the proposed new technological system (Cummings, 2003). The Ethical Factors analysis is critical because the effects and consequences of a decision made with the proposed system can be severe, such as loss of life.

Figure 2: An example of a communication flow map (Cummings, 2003).
Work Domain Analysis and Constraint-based Task Analysis

The CWA’s Work Domain Analysis (WDA) focuses on understanding the relationships between subsystems and components (Vicente, 1999). The WDA, by itself, can be considered a CTA technique. The WDA is classifiable as a Goal-driven CTA technique and, therefore, is discussed in the Goal-driven CTA technique section later in this chapter. The CWA’s Constraint-based Task Analysis (CbTA) is designed to model the process of going from decisions to knowledge states as a task is completed (Vicente, 1999). By itself, the CbTA can be considered an Information-driven CTA technique and, therefore, is discussed in the Information-driven CTA technique section later in this chapter.

Analysis of Effective Strategies, Local Social & Organization Factors, and Worker Competencies

The CWA’s Analysis of Effective Strategies is designed to represent the methods by which particular tasks represented in the CbTA can be achieved independent of who is executing the tasks (Vicente, 1999). The CbTA technique focuses on representing the products of tasks; whereas, the Analysis of Effective Strategies focuses on representing the process of a task.

The CWA component, Analysis of Local Social & Organization Factors, is intended to capture the communication, cooperation, and authority relationships between workers and other workers and the system. The result describes how tasks can be allocated and how Effective Strategies may be distributed across workers and the system.
The final CWA component, Worker Competencies, is designed to capture the set of constraints associated with the workers themselves, such as capabilities and limitations. The focus of Worker Competencies is to identify the knowledge, rules, and skills that workers should have to effectively perform their various functions and responsibilities.

Categorizing Cognitive Work Analysis

As a whole, CWA is classifiable as a Crossover CTA technique because its various component methods encompass both Goal-driven and Information-driven CTA approaches. The CWA methods, however, are often performed individually (Kaber, Segall, Green, Entzian, & Junginger, 2006; Naikar, Hopcroft, & Moylan, 2005; Vicente, 1999). Individually, only three of the seven CWA methods are CTA techniques; namely, WDA, CbTA, and Analysis of Effective Strategies (Vicente, 1999). The other four methods, by themselves, are not cognitive task analysis techniques as they focus on system aspects other than tasks (Vicente, 1999; Cummings, 2003). Two of the three CTA techniques are discussed in this chapter by themselves as CTA techniques: WDA and CbTA. The Analysis of Effective Strategies is not discussed in the review of CTA techniques because its scope is a single decision and, therefore, it is not designed to model the entire system. The two CWA methods that are discussed in this chapter do not belong to the same CTA group: WDA is a Goal-driven CTA technique, and CbTA is an Information-driven CTA technique. Part of the appeal of CWA is that the methods analyze the system from different perspectives.
Goal-driven CTA Techniques

Goal-driven CTA techniques are focused on modeling a system’s goal and sub-goals through a part-whole relationship. Many CTA techniques can be classified as goal-driven (Yates, 2007); however, two techniques have seen widespread use when specifically modeling complex human-machine systems and are, therefore, relevant to modeling the CBRNE response system. The two techniques are the Hierarchical Task Analysis (HTA) (Shepherd, 1998, 2000) and Work Domain Analysis (WDA) (Vicente, 1999). The HTA technique is one of the most common CTA techniques and is based on the concept that task goals and plans can be arranged in a hierarchical fashion (Annett, 2003). The WDA is less common (Jamieson, Miller, Ho, & Vicente, 2007) and is designed to model the constraints of the work domain in which the goals and plans operate (Vicente, 1999). The WDA is, therefore, broader than the HTA in terms of what is included in the analysis.

It must be noted that in Jamieson et al. (2007), the HTA and WDA techniques are not placed in the same group. This dissertation does not dispute Jamieson et al.’s (2007) separation, as the HTA and WDA techniques have distinctly different approaches to modeling the system, which is how their categorization is organized. However, Jamieson et al. (2007) do note that both analyses provide “an understanding of the ways in which known goals can be achieved in various contexts of use,” that is, the two techniques are goal-driven, which is how this dissertation has categorized them. Furthermore, both
techniques have a part-whole relationship between the elements, another feature of goal-driven CTA techniques.

Goal-Directed Task Analysis (GDTA) (Endsley et al., 2003) and Goals, Operators, Methods, and Selection rules (GOMS) (Card, Moran, & Newell, 1980, 1983) are also goal-driven CTA techniques. The GDTA is designed to identify the users’ goals, decisions, and the information needed to support making those decisions (i.e., the Situational Awareness (SA) requirements) (Endsley et al., 2003). The GDTA technique incorporates information that drives how the decisions are made, thus it is classified as a crossover CTA and is discussed in Crossover CTA Technique section later in this chapter. The GOMS technique was established to model a user’s procedural knowledge (Kieras, 2003). GOMS has properties similar to HTA (Annett, Duncan, Stammers, & Gray, 1971; Kirwan & Ainsworth, 1992), but the scope of a single user’s procedural knowledge renders GOMS very difficult to apply to modeling the entire CBRNE response systems that entails hundreds of users and ill-defined procedural knowledge. Therefore, the GOMS technique will not be discussed further.

Hierarchical Task Analysis Technique

Hierarchical Task Analysis (HTA) has a long history with many variations, extensions, and simplifications (Annett, 2003). The term encompasses ideas developed by Annett and Duncan in the late 1960’s and early 1970s (Annett & Duncan, 1967; Annett et al., 1971; Duncan, 1972, 1974). The concept of HTA is to define tasks via a hierarchy of goals and plans, which are composed of subordinate goals and plans. Often
goals at higher levels are more abstract or general, while goals at lower levels resemble tasks or functional steps more directly. However, the actual definition of these nodes and the word “task” itself is somewhat fluid and has seen considerable debate (Shepherd, 1998, 2000).

The HTA technique is a directed graph with a root node and subsequent child nodes linked together by a part-whole relationship. These nodes can represent goals, tasks, plans, and behaviors (Shepherd, 1998, 2000). Regardless of how the nodes are defined, they represent a function that must be completed in order to achieve the objective of the parent node (Figure 3). The sheer flexibility of the HTA technique and its focus on understanding the entire system makes it applicable to the CBRNE response system. Its focus on goals makes it easy to understand and communicate to subject matter experts.

The HTA technique does have a number of limitations in regard to analyzing the CBRNE response system. The HTA technique provides limited mechanisms for scheduling functions, no explicated representation of parallelism, and no information required for decision-making or SA, all of which are vitally important to the CBRNE response system. The HTA provides scheduling only through the introduction of a plan as shown in Figure 3. Figure 3 represents a HTA for the task “Care for and treat babies” from Shepherd (1998) and the plan specified the standard ordering of the functions. The plan is fine for one structured execution of tasks; however, if the system is less structured or there are many possible valid execution sequences, then the plan concept becomes very limiting in representing partial scheduling.
Work Domain Analysis

CWA has many components, including the WDA, which is designed to identify the goal-relevant structure of the system being controlled, independent of any particular worker, automation, event, task, goal, or interface (Vicente, 1999). The WDA has a similar scope as the HTA, that is, the entire domain. The purpose of the WDA is to model the constraints of the work domain in order to create a detailed understanding of the system. The model technique used to perform a WDA has traditionally been an abstraction hierarchy represented as an abstraction-decomposition space, also collectively referred to as an Abstraction-Decomposition (J. Rasmussen, 1985) or simply a WDA (Vicente, 1999). The Abstraction-Decomposition was developed and formalized by

Figure 3: A HTA Example for the Care for and treat babies task from Shepherd (1998).
Rasmussen over a number of years (J. Rasmussen, 1976, 1985, 1988; Moray, J. Lee, Vicente, B. G. Jones, & J. Rasmussen, 1994) and has been used by many individuals (Cummings, 2003; Krosner, Mitchell, & Govindaraj, 1989; Naikar et al., 2005; Gersh, Cropper, Fitzpatrick, McKerracher, Montemayor, & Ossing, 2005; Lind, 2003).

The Abstraction-Decomposition is similar to HTA; however, the Abstraction-Decomposition has two dimensions that represent different relationships and specified levels of abstraction (as shown in Figure 4). The two dimensions are a means-end relationship along the vertical axis and a part-whole relationship along the horizontal axis. For example in Figure 4, the vertical axis represents the means-end relationships present in the system. The horizontal axis’ left most column, in Figure 4, is the whole tactical Tomahawk System and the columns to the right represent components of this system (Cummings, 2003).

The horizontal axis, and therefore the horizontal hierarchy, is in essence a HTA. Where the Abstraction-Decomposition technique differs from, and possibly improves upon, the HTA is in its vertical hierarchy. The vertical hierarchy represents the system through a means-end relationship. The standard five levels, (although five levels are not required) that comprise the vertical hierarchy are functional purpose, abstract functions, generalized functions, physical functions, and physical form (Lind, 1999; J. Rasmussen, 1986). The five levels may also have different labels that essentially represent the same meaning. These alternative labels are goal, priorities measures, general functions, processes, and objects (Cummings, 2003).
<table>
<thead>
<tr>
<th>Tactical Tomahawk System</th>
<th>Monitoring Subsystem</th>
<th>Retarget Subsystem</th>
<th>Components</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Goal</strong></td>
<td>To support battlefield commanders</td>
<td>• Accuracy of information</td>
<td>• Missiles redirected as quickly as possible without error</td>
</tr>
<tr>
<td><strong>Priority Measures</strong></td>
<td></td>
<td></td>
<td>• Best possible trade-off decision is made in a retargeting scenario</td>
</tr>
<tr>
<td><strong>General Functions</strong></td>
<td>Monitor all critical Tomahawk functions and mission data during a strike</td>
<td>Redirect missiles in-flight to either a preprogrammed flex target or an emerging target</td>
<td></td>
</tr>
<tr>
<td><strong>Processes</strong></td>
<td>• Missile health &amp; status reports, BDI imagery, &amp; transmissions.</td>
<td>• Select optimal missile(s) for retargeting</td>
<td>• Temporal attributes</td>
</tr>
<tr>
<td></td>
<td>• Temporal elements</td>
<td>• Retarget missiles through both data link and manual entry</td>
<td>• Geo-spatial elements</td>
</tr>
<tr>
<td></td>
<td>• Communications</td>
<td></td>
<td>• Object information</td>
</tr>
<tr>
<td></td>
<td>• Spatial attributes of missiles</td>
<td></td>
<td>• Communications Data</td>
</tr>
<tr>
<td><strong>Objects</strong></td>
<td></td>
<td></td>
<td>• Retargetable Missiles</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>• Loiter Missiles</td>
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<td></td>
<td></td>
<td></td>
<td>• Emergent Targets</td>
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<tr>
<td></td>
<td></td>
<td></td>
<td>• Flex Targets</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>• Waypoints</td>
</tr>
</tbody>
</table>

**Figure 4: A WDA example (Cummings, 2003).**

The HTA has been compared with the Abstraction-Decomposition (or WDA) (Jamieson et al., 2007; Miller & Vicente, 2001). Although the two techniques have their differences, their differences are complementary (Jamieson et al., 2007). The Abstraction-Decomposition was concluded to provide deeper knowledge and a fuller set of system constraints and capabilities; whereas, the HTA technique was assessed to be a more procedural, human-centered approach that is easily learned and applied (Miller & Vicente, 2001). The Abstraction-Decomposition provides deeper knowledge but the deeper representation, fundamentally, comes at the cost of human readability. This readability may become an issue when interacting with subject matter experts and designers unfamiliar with the Abstraction-Decomposition technique’s double hierarchy, as was the case with the CBRNE Response System. Unfortunately, the Abstraction-Decomposition technique, as with the HTA technique, provides no inherent mechanisms...
for scheduling, representing parallelism, and information required for decision-making or SA.

Information-driven CTA Techniques

Information-driven CTA techniques are focused on modeling a path or paths in which information or knowledge is directed to achieve the overall task. Fewer CTA techniques can be classified as information-driven than can be classified as goal-driven (Yates, 2007). There is one information-driven CTA technique, Constraint-based Task Analysis (CbTA), which has seen use in modeling complex human-machines (Naikar, Moylan, & Pearce, 2006; Vicente, 1999). The CbTA technique is designed to model the process of going from decisions to knowledge states as a task is completed (Vicente, 1999).

Another technique called the Sensor-Annotated Abstraction Hierarchy (Reising & Sanderson, 2002a, 2002b) is information-driven but may not be classified as a CTA technique because of its focus on the physical system. The Sensor-Annotated Abstraction Hierarchy focuses on a defined set of sensors and not the cognitive processes, decisions, and judgments of the system’s users. The Sensor-Annotated Abstraction Hierarchy is not designed to analyze a system composed mostly of humans with an undefined and changing set of information gathering actors (i.e. sensors), as is present in the CBRNE response system. For example, in the CBRNE response system a group of responders will search for victims but the number of responders (i.e. sensors) and the types of equipment (i.e. sensors) they will have available will vary greatly between and within responses.
This mismatch regarding the targeted domain causes the Sensor-Annotated Abstraction Hierarchy technique to be untraceable at this scale and for the CBRNE response system at this time, but it may become relevant in the future. For example, the Sensor-Annotated Abstraction Hierarchy may be used to model the flow of information used by a robot as it performs a task. Figure 5 provides an example of how a Sensor-Annotated Abstraction Hierarchy may represent the flow of information during a visual reconnaissance task for an unmanned helicopter. In this example, the objects represent different low-level physical subsystems (e.g. internal gyro) and as one moves up the abstraction hierarchy the tasks become more complex (e.g. maintain appropriate position).
Figure 5: The Sensor-Annnotated Abstraction Hierarchy for a hypothetical unmanned helicopter used for visual reconnaissance.
Information-driven CTA techniques are related to the dataflow techniques used in software, signal processing, and embedded system designs (Johnston et al., 2004). Whereas CTA techniques aim to depict the path of information used to make decisions by humans, Visual Dataflow techniques aim to depict the path of information used to make decisions by machines (Diaper, McKearney, & Hurne, 1998). However, as these machines perform more cognitive tasks that where once performed by humans, the distinction between techniques that model human cognitive tasks and those that model machine cognitive tasks diminishes. Therefore, Visual Dataflow techniques are very applicable for representing the path of information for cognitive tasks performed by either humans or machines. Visual Dataflow techniques have been used to as a CTA technique, but such usage is rare (Diaper et al., 1998; Flach, Mulder, & van Paassen, 2004). The Visual Dataflow techniques, although not traditionally viewed as CTA methods, will be reviewed in this section.

Constraint-based Task Analysis

The Constraint-based Task Analysis (CbTA) is an information-driven CTA technique based on a two-step action-knowledge structure. The actions are linked together in an action-means-end relationship (Vicente, 1999). This relationship forms the foundation of the CbTA. The CbTA model provides some mechanisms for the scheduling of actions because of its inherent relationship type and the modeling techniques it traditionally employs.
The traditional modeling language for a CbTA is a Decision Ladder (J. Rasmussen, 1986). The Decision Ladder is a two-step structure graph based on finite state machines that permit only one state to be active at once. Figure 6 provides an outline of a typical DL reference. The two-step structure is comprised of an information-processing activity node or function node, followed by a state of knowledge node. For example, the function node can be “do homework” and the resulting state of knowledge can then be “homework is finished.” The CbTA’s Decision Ladder technique only permits one knowledge state or information production from each function node. Decision Ladders’ function node can be connected to several knowledge states other than the primary proceeding knowledge state (via shunt connections); however, only one of these knowledge states will be entered after the function is performed. Knowledge states can also be connected together through leap connections; however, again only one knowledge state can be active at any given time. A knowledge state may imply that the information items required to do the action represented in the action node, but it is not explicit. For example, the “homework is finished” knowledge state implies that the function “do homework” took the assignment as an input and produced the homework document as an output information item.
The Decision Ladder technique has a number of issues that have caused others to modify or replace it (P. Jones, Patterson, & Goyle, 1993). Decision ladders are inherently awkward at expressing parallelism or complex partial order scheduling (P. Jones et al., 1993). This awkwardness is a result of Decision Ladder being fundamentally based on finite state machines, which allow only one state to be active at a time. When a Decision Ladder involves more than one decision sequence or the decisions overlap in time, the finite state machine model is inadequate, as it cannot represent parallelism succinctly (Johnston et al., 2004). Jones et al. (1993) extended Decision Ladders for use with two
parallel operators; however, this is still inadequate for the CBRNE response system, as it potentially requires hundreds, if not thousands, of operators.

Visual Dataflow techniques

Although Visual Dataflow techniques are designed to model the decisions made by a system, the basic approach can be applied to modeling cognitive tasks. Indeed, it can be argued that the basic principle enshrined in the Visual Dataflow techniques forms the basis of the CbTA technique. Visual Dataflow techniques are based on dataflow languages.

Dataflow languages were developed in response to the belief that von Neumann processors and their corresponding languages were inherently unsuitable for the deployment of parallelism (Dennis & Misunas, 1974). Dataflow was designed to embrace parallelism by focusing on the data and executing instructions as soon as a function’s local data was available. Dataflow imposes a partial ordering constraint on execution, thereby allowing parallelism to be exploited.

Since the 1990’s, dataflow languages have become visual in nature and these newer versions are called Visual Dataflow programming languages (Johnston et al., 2004). The Visual Dataflow programming languages have been refined and developed by a number of individuals over time (see Johnston et al. (2004) for a review). During the development of Visual Dataflow programming languages, the focus slowly shifted from exploiting parallelism to data abstractions due to the advantages that data abstractions provided to the developer during the software development lifecycle (Baroth &
Baroth and Hartsough (1995) reported that developing systems in a Visual Dataflow programming language, namely LabVIEW (2008), was considerably faster, four to ten times faster, than developing systems in procedural functional languages such as C. They attributed the speed improvement to dataflow’s ability to show the information processing explicitly and visually. This shift in focus to abstraction and visually representing information processing makes Visual Dataflow an intriguing analysis for modeling the CBRNE system response.

The basic Visual Dataflow technique produces a model that is a directed graph with the nodes representing instructions and the arcs representing the data dependencies between instructions (Dennis, 1974; Johnston et al., 2004) (Figure 7). The data flows on the arcs and conceptually act as data tokens or packages that queue before an instruction in an unbounded first-in, first-out queue (Kahn, 1974). Node execution requires two steps: the first is to wait passively until all required incoming data is present, and then secondly to process the data tokens by placing the output data tokens on all appropriate outgoing data arcs (Dennis, 1974; Johnston et al., 2004). This type of node execution is called data-availability-driven approach (Johnston et al., 2004). For example, the result of $X + Y$ in Figure 7 flows as a token on the arc from the “+” to the “*” function nodes and is queued there until $Y / 10$ produces its token, thereby fulfilling the “*” function node.
Over time, the expressiveness of the dataflow language has increased so that any arbitrary system can be represented in a dataflow abstraction (Johnston et al., 2004). Much of the work to date has been related to implementing a dataflow language on hardware or maximizing parallelism. Neither of these areas is of interest for the CBRNE response system analysis, as the analysis is intended to guide development and not employed as a pseudo programming language. However, a number of papers and ideas have increased or addressed aspects of dataflow’s modeling expressiveness (e.g. how and with what detail level it can model) that will be addressed in the remainder of this section.

Enabling execution control in dataflow models requires the addition of two node types: the SWITCH and the SELECT nodes (Johnston et al., 2004). Both of these nodes perform an if-then-else execution based on an input control signal. The node SWITCH determines which outgoing arc receives the incoming arc’s data. The node SELECT determines which incoming arc provides the data to the outgoing arc.
Another extension to the basic dataflow language is the multidimensional dataflow (Murthy & E. Lee, 2002). Multidimensional dataflow addresses the concern that the basic dataflow arcs are modeled after first-in first-out queues, which are inherently one-dimensional. Multidimensional dataflow increases the dataflow expressiveness by transforming the first-in first-out queues into arrays and introduces the concept of queue sampling windows (Murthy & E. Lee, 2002). A queue-sampling window allows the function node to determine its output based on the history of that type of input and not a single sample as in the original dataflow technique. For example, Figure 8 depicts a multidimensional dataflow function node that performs the average operation on an arbitrary length vector, which is something that a standard dataflow cannot express as succinctly. The multidimensional feature is important to the CBRNE response system modeling as most decisions are based on a historical view of the information, which facilitates better quality decisions. For example, in the CBRNE response system individual hazard readings are transformed into a hazard report not as individual readings, but as a collection. This collection of readings is clearly represented in a multidimensional dataflow concept.
Figure 8: A multidimensional function node that takes a vector of variable length and computes the mean.

The Visual Dataflow technique still has a hierarchical nature, similar to the HTA technique; however, the dataflow hierarchy is determined by the flow of information, not the decomposition of goals or tasks. Therefore, the Visual Dataflow technique does not clearly represent the reason or purpose motivating the existence of each information-processing or function node. Furthermore, the relationship between the information consumed at each node and SA is unclear, in part because the Visual Dataflow technique was not designed to facilitate or consider SA.

Crossover CTA Techniques

CTA techniques that are primarily goal-driven CTA techniques or information-driven CTA techniques that also incorporate aspects of the other analysis techniques are termed crossover CTA techniques. There are very few unified crossover techniques, as there are rarely goal-driven CTA techniques explicitly concerned with information or information-driven CTA techniques that are concerned with goals or decision questions.
A limited number of crossover techniques exist in part because often one will perform a goal-driven CTA and then use the resulting model as the bases for ascertaining information requirements, which are then depicted in tables or lists (Annett, 2003; Miller & Vicente, 2001; Jamieson et al., 2007). Another approach to understanding both goals and information related to a task has been to perform both a goal-driven and an information-driven technique. CWA does this by performing both a WDA and a CbTA (Vicente, 1999); however, it is left to the system designer to relate the results of the two techniques. The pentanalysis technique, like the CWA, also employs both a goal-driven and an information-driven technique, but provides a formal mechanism to relate the results of the two techniques (Diaper et al., 1998). The pentanalysis technique was designed to bridge the gulf between task analysis and data flow analysis (Diaper et al., 1998). The pentanalysis technique essentially employs a special table that relates the task analysis to the data flow analysis.

The hybrid CTA method proposed by Nehme, Scott, Cummings, and Furusho (2006) and extended by Almirao, da Silva, Scott, and Cummings (2007), like CWA, use several methods to represent both goals and information. The hybrid CTA uses four methods: a scenario task overview, an event flow diagram, a list of situation awareness requirements (i.e. information requirements), and decision ladders (i.e. CbTA). The hybrid CTA uses the scenario task overview and the event flow diagram to represent goals and the list of situation awareness requirements and decision ladders to represent information.

The CWA, the pentanalysis technique, and the hybrid CTA do not present their goal-driven and information-driven components in one coherent model. In contrast, a
crossover CTA techniques, present a unified, explicit representation of both the goals and information in one model. The Goal-Directed Task Analysis (GDTA) technique represents both goals and information in one model and is therefore a crossover CTA technique. The GDTA technique is applicable to systems such as the CBRNE response system (Endsley et al., 2003) in part because GDTA focuses on situational awareness (SA) by representing information requirements, for certain goals, in its goal hierarchy.

*Goal-Directed Task Analysis*

Endsley et al. (2003) recommend using Goal-Directed Task Analysis (GDTA) for identifying the system’s users’ goals, decisions, and the information needed to support making those decisions, namely the Situational Awareness (SA) requirements. This method seeks to discover the ideal information the user would like to know in making each decision required to complete each goal. The GDTA technique is therefore not bound to what currently exists, and leaves room to identify potential system improvements (Endsley et al., 2003).

The basic framework of Goal-Directed Task Analysis (GDTA) is a goal-driven CTA where nodes represent goals, decisions, and actions (Endsley et al., 2003). The links between the nodes represent part-whole relationships. The GDTA technique is structurally similar to a HTA, and it inherits much of the HTA technique’s flexibility. The GDTA, however, does not use plans, like HTA, and therefore does not represent scheduling or parallelism as succinctly as do the information-driven CTA techniques. The GDTA extends the basic HTA structure with the representation of information
requirements and decision questions. The GDTA has been compared to the WDA and has been found to be complimentary (Humphrey & Adams, 2008; Kaber et al., 2006; Adams et al., 2008).

GDTA is considered a crossover CTA because it augments a goal node with information that drives the outcome to that goal. The information represents both the data required to perform the node’s goal and the data required to maintain the user’s situational awareness (SA) relating to that goal (Endsley, 2001; Endsley et al., 2003). The concept of SA has swayed between being focused almost exclusively on awareness to be more balanced between situation and awareness (Flach et al., 2004). Therefore, each GDTA node represents not only a simple goal, but also a decision, and the information requirements needed to support SA and the decision making process in order to achieve the goal (Flach et al., 2004). Figure 9 depicts an example GDTA with two levels of goals, decision questions, and SA requirements from Kaber et al. (2006).

Figure 9: An example GDTA from Kaber et al. (2006).
Flach et al. (2004) extended the GDTA technique by creating levels of information requirements that better address the balance between situation and awareness. The information requirement levels proposed are very similar to the abstraction levels in the WDA abstraction decomposition space. The levels proposed are functional purpose, functional measurement, functional organization, and physical function (Flach et al., 2004). The physical function is defined as the logical decomposition of the information flow through the network of functions. At this information level Flach et al. (2004) borders on incorporating a data flow model into GDTA; in fact, it can be argued that a data flow model is the most appropriate model to express the concepts outlined at the physical function level. The physical function level of the information requirements provides the means of representing a partial order of the information requirements. However, it is unclear whether merely expressing the information requirements with a partial ordering will actually mitigate the overall GDTA’s inability to represent scheduling and parallelism.

The GDTA technique produces a model that contains goals, tasks, and information requirements. The GDTA, however, does not represent scheduling and parallelism as do the information-driven CTA techniques. Flach et al.’s (2004) extension mitigates this issue to some extent, but not through one integrated model. The GDTA’s ability to represent both goals and information, along with its focus on SA makes it applicable to the CBRNE response system.
Cognitive Task Analysis Techniques Applied to Robotic Systems

A number of CTAs for various aspects related to emergency response exist (e.g. A. C. Jones & McNeese, 2006; Ntuen, Balogun, Boyle, & Turner, 2006); however, these analyses do not focus on robotic systems. A few researchers have applied CTA techniques to analysis robotic systems. The two most common CTA techniques employed have been GDTA and the CWA’s WDA. Riley, Murphy, and Endsley (2006) conducted a GDTA on tasks involving an existing urban search and rescue ground based robot. Riley and Endsley (2005) performed a GDTA for a futuristic ground based robot control task involving collaboration between robots in a minefield breach task. Adams et al. (2008) conducted GDTA and CWA for a wilderness search and rescue aerial robot that appears to be the first to inform a real aerial robot system. Rasmussen (1998) conducted a CWA on a command and control information system that utilized aerial robots for suppression of enemy air defense missions. Gonzalez Castro, Pritchett, Bruneau, & Johnson (2007) employed a CWA for developing UAV procedures, functions, and a proposed ground control station. Nehme et al. (2006) and Almirao et al. (2007) have developed a hybrid CTA technique and have employed it for futuristic aerial robotic systems. This hybrid CTA is similar to Cummings modified CWA (2003) but employs fewer and slightly different steps (see Crossover CTA Technique section above). This dissertation is the first to apply CTA methods to the CBRNE response system for the purpose of incorporating robotic technology.
Summary

There are two purposes in analyzing the CBRNE response system. The first is to understand how the current CBRNE response system operates. The second is to inform the design and implementation of new robotic technology along with how the new technology will integrate and alter the current system. Conducting a Cognitive Task Analysis (CTA) has been shown to assist in developing and introducing new robotic technology by facilitating an understanding of the domain and the appropriate robot tasks (Adams, 2005; Almirao et al., 2007; Adams et al., 2008). The previous sections discussed Goal-driven, Information-driven, and Crossover CTA techniques. Each category has both strengths and limitations. Goal-driven CTA techniques, such as HTA and the CWA’s WDA, model goals very well and, to a lesser degree, the reasons or decisions driving the goals, but have limited abilities to represent ordering, parallelism, or SA information requirements. Information-driven CTA techniques, such as the CWA’s CbTA and Visual Dataflow, model the flow of information and represent both ordering and parallelism; however, these techniques are limited in representing the reasons or decisions driving the path of information or SA information requirements. The Crossover CTA technique, GDTA, models goals, the reasons or decisions driving the goals, and SA information requirements; however, GDTA does not represent ordering or parallelism.

The limitations inherent in the discussed CTA techniques led to the use of a combination of techniques to analyze the CBRNE response system. The reasons for choosing the combination of GDTA and CWA, the methodology of applying these techniques, and the results are presented in Chapter III. The results of GDTA and CWA were used to apply a new technique, Cognitive Information Flow Analysis, which is
based on the expressive power of Visual Dataflow. Cognitive Information Flow Analysis is presented in Chapter V.

Visualizing the System

The proposed robotic technologies for the CBRNE response system will use computer-based visualizations for both command and control of the robots and feedback from the robot. This section presents literature related to visualizing a system such as the CBRNE response system.

The management and understanding of the CBRNE response system must evolve as current methods for handling the human and equipment response are based on limited orally communicated or directly observable real-time information (e.g. “Sir, I see a possible secondary hazard”) and static support information (e.g. static road maps, past aerial photos, current fly over images, field manuals). The new complex human-machine system generates and captures volumes of information not communicated or represented in the existing system that may overwhelm the decision-makers without an evolution in the data management, understanding, and visualization techniques.

One technique for managing and understanding emergency incidents is to use computer-based visualizations to present the captured information to support decision-making. The proposed CBRNE response system visualization is a direct-able visualization, which is different from interactive or dynamic visualizations. A dynamic visualization contains elements that change with time. An interactive visualization contains elements that can be directly manipulated, or the information is under full
ownership of the user (Jul & Furnas, 1998), meaning that the system cannot change the information autonomously. An interactive visualization by definition changes over time and therefore is also dynamic. A directable visualization does not allow the user to have full ownership of the elements, meaning the user can only specify what the elements should do, not what the elements will do. Elements in the CBRNE response system visualization are not under full user ownership because the visualization elements are both in the real world and have some level of cognitive abilities to choose their own actions. For example, elements that represent robots can accept commands from the user, but the outcome of the commands are uncertain as the robot may encounter any number of problems (e.g. an unknown obstacle). This lack of full ownership in a directable visualization system makes the interaction and visualization more complicated than in an interactive system. The added complication arises as consequences of a command are uncertain and are only revealed as time passes.

The employed visualization needs to be multi-scale, a consequence of modeling a city-scaled event with small-scaled details. Multi-scale in this context means that information exists at multiple levels of detail and that these detail levels are not presented all at once (Jul & Furnas, 1998). The multi-scale feature introduces two related concepts: zoom and information scale. Zoom means that level of visualization detail can change in a navigable manner. Information scale is the concept that a particular piece of information is not necessarily present at all levels of detail because the information may be too small, too large, or too dense to be presented at a particular level of detail. For example, if the visualization displays the entire state of Tennessee, an individual house is too small to be visible (i.e. the information is smaller than the smallest unit of
presentation detail, in this example, a pixel). Sometimes a multi-scale system is called a Zoomable User Interface to highlight the zooming capability over the information scale (Pook, Lecolinet, Vaysseix, & Barillot, 2000).

A CBRNE response system visualization will be designed to support incident management and must provide three features: immediacy, relevancy, and sharing (Cai, Sharma, MacEachren, & Brewer, 2006). **Immediacy** is the concept that the system must provide information on-demand, since time is a precious commodity in emergency incidents. **Relevancy** means that the information content and presented form must fit the current needs of the decision-makers. **Sharing** means that the system needs to disseminate information to multiple decision-makers. From these three features, arise three problem areas that are a focus of this dissertation. The three problem areas are information abstraction (a combination of immediacy and relevancy), relaying information to different user levels (sharing), and temporal navigation (a combination of immediacy and relevancy).

**Information Abstraction**

Information abstraction represents one problem area related to the immediacy and relevancy requirements. The classic situation occurs when there are hundreds or more information items displayed on a screen simultaneously such that they clutter the screen to the point that the visualization is useless. The purpose of information abstraction is to reduce this clutter so that the visualization conveys more useful and relevant information. Information abstraction is critical to decision making as its absence means that the
decision-maker must manually parse the important information from the unimportant information (if it is possible) and manually group related information. Both of these tasks are cognitively demanding (Wickens, J. D. Lee, Liu, & Gordon-Becker, 2003). Furthermore, some information details cannot be represented at a particular scale, due to limitations in screen size, without abstraction (Woodruff, Landay, & Stonebraker, 1998).

The problem is how to abstract information that has spatial \((x, y)\), elevation \((e)\), temporal \((t)\), information scale \((s)\), and semantic meaning \((m)\) \((x, y, e, t, s, m)\) to reduce clutter thereby providing a relevant visualization for on-demand decision making. Ellis and Dix (2007) identified and reviewed eleven cluster reduction techniques in three categories: appearance (i.e. sampling, filtering, change point size, change opacity, and clustering); spatial distortion (i.e. point/line displacement, topological distortion, space-filling, pixel-plotting, and dimensional reordering); and temporal (i.e. animation.) The systems based on geographic maps, like the CBRNE response system, generally employ three basic operations to reduce clutter: selecting information to present (i.e. sampling and filtering); grouping information together, if applicable (i.e. point displacement and clustering); and displaying the information with a shape (i.e. space-filling, change point size, and change opacity) (Woodruff et al., 1998; Ellis & Dix, 2007). Others have also focused on these operations: selection (Cui, Ward, Rundensteiner, & Yang, 2006; Ellis & Dix, 2006a), grouping (Jul & Furnas, 1998; Ellis & Dix, 2006a), and shapes (Cui et al., 2006; Ward, 2002; Humphrey, Gordon, & Adams, 2006). However, solutions have either relied completely on a priori information item knowledge (Jul & Furnas, 1998; Cai et al., 2006; Ward, 2002), no item knowledge (Ellis & Dix, 2006a), or require the end user to completely specify the solution (Woodruff et al., 1998).
Solutions that rely completely on a priori information item knowledge use a collection of preprogrammed rules to determine how information should be abstracted, grouped, and displayed. These rules require that the designer anticipate and organize all possible information that the system may encounter in ways that support the user's decision-making. In highly dynamic systems, both in terms of the types of information and the types of decisions to be made, developing rules for all possibilities is improbable and leads to brittle systems. The CBRNE response system is such a dynamic system and, therefore, a method for information abstraction needs to be designed that is more flexible than a specific set of rules while being applicable to novel information and unanticipated decision-making tasks.

Random sampling (Ellis & Dix, 2006a) is a solution that relies on no item information, as it simply displays a random subsection of the available information elements to reduce clutter. While this method does reduce clutter, the more diverse the information types the more likely the random subsection will not contain elements necessary for a particular decision. Random sampling is an inherently limiting abstraction technique, as it is most applicable when information items are homogenous in type. This is not the case in the CBRNE response system, which may potentially include hundreds of information item types (e.g. robots, responders, bombs, and vehicles).

Solutions that require the end user to completely specify the information abstraction are not appropriate for real-time critical decision-making systems like the CBRNE response system. These solutions are most appropriate when the end user can afford the time at the beginning of the visualization usage to discover the parameters that lead to an affective information abstraction. The time at the beginning of a CBRNE
response is the most critical (Howe, 2004) and forcing the end user to use that time to deal with the working of the system’s visualization instead of making critical life changing decisions is reckless. It is well known that systems that are difficult to use are typically not adopted, thus relying on large amounts of user specification at the start of an incident is not an option. However, this is not to say that any information abstraction solution for the CBRNE response system cannot be controlled or modified by the end user, but that explicit modification of the visualization should be optional and seldom necessary.

Relaying Information to Different User Levels

The sharing of information across users represents the second problem area and focuses on how to relay or share information to different user levels. User Levels have been based on the taxonomy defined by Scholtz (2003) which was extended by Goodrich and Schultz (2007). Six human robot interaction roles were defined: supervisor, operator, mechanic, peer, information consumer, and bystander. Humphrey and Adams (2008) add one additional user level, the abstract supervisor as discussed in Chapter IV. Information sharing in multi-scale and incident systems is a widely covered topic. Methods include shared space (Tomaszewski & MacEachren, 2006), shared flags (Tomaszewski & MacEachren, 2006), instant messaging (Meissner, Wang, Putz, & Grimmer, 2006), activity sessions (Tomaszewski & MacEachren, 2006), and large-scale displays (Baudisch, Good, Bellotti, & Schraedley, 2002; Rauschert, Agrawal, Fuhrmann, Brewer, Sharma, Cai, et al., 2002).
*Shared space*, sometimes called a project workspace or shared workspace, is a visualization system that acts as if all the users are sharing one program and one screen even though the users are distributed geographically in different locations (Tomaszewski & MacEachren, 2006; Cai et al., 2006). This technique allows every user to see explicitly what every other user is doing; however, the technique has strong limitations. The shared space technique does not allow users to view different areas of the visualization at the same time and only allows users to share information in real time. Shared spaces works by specifying the six components \((x, y, e, t, s, m)\) as constants for every user, thereby making sharing simple but inflexible and limiting. *Large-scale displays* are a functional equivalent to shared spaces, except that instead of the users being distributed geographically, all users are in one location and the screen is very large in order to accommodate many people viewing it simultaneously (Baudisch et al., 2002; Rauschert et al., 2002).

The *shared flags* technique allows users to create new artifacts in the visualization to highlight ideas to be shared (Tomaszewski & MacEachren, 2006). Unlike shared space, the users are allowed to view different visualization areas simultaneously; however, the cost is that other users may be unaware that the flag has been created or how to navigate to the flag in another area of the visualization that differs from their location in the visualization. Another limiting feature is that the flags are only place-markers and do not eloquently or clearly capture the reason or the change of events that lead to the flag’s creation. Therefore, shared flags do not share directly any of an information element’s six components, but instead add new artifacts and leave to the users the task of ascertaining the artifact’s relationship to the real information entities.
The *instant messaging* technique allows users to write text messages to one another to express ideas (Meissner et al., 2006). This technique can express any idea and can share all six information components, but only indirectly. The user receiving this shared information must translate and correlate the text messages back into the information entities they represent. This translation, both into text and back again, is slow and can introduce understanding errors and misconceptions. For example, text from one user representing a particular information item may be interpreted by another user as a different information item if the text is not precise enough.

The *activity session* concept creates an artifact to represent a high-level, logical collection of information entities that illustrate an idea or problem (Tomaszewski & MacEachren, 2006). The concept of an activity session discusses sharing at least five [*x, y, e, t, and m*] information components, but the mechanisms the authors choose are limiting and do not allow all information components to be directly shared. Tomaszewski and MacEachren (2006) use shared annotations with the ability to “play” these shared annotations in time order as the means to facilitate activity sessions. *Shared annotations* are shared flags that provide extra text (Tomaszewski & MacEachren, 2006). Once again, information is not directly shared, but is indirectly shared through artifacts, thus requiring users to map the artifacts to the related information entities. The artifacts in the activity session, however, do have a timeline.
Temporal Navigation

The last problem area is temporal navigation or how the user will explore time in the CBRNE response system. Navigation through time is often aided with time marks or the highlighting of key frames or time segments (Wickens et al., 2003). A classic example of time marks is the scenes in the scene selection menu on DVDs. Research exists for navigation through time (Dachselt & Weiland, 2006) and this dissertation does not propose a new navigation through time mechanism, but rather a means of creating time marks automatically (see Chapter VI for details).

Summary

This proposed research to develop a CBRNE response system that includes robotic technology will use computer-based visualizations. Those visualizations must provide three features: immediacy, relevancy, and sharing and address three problem areas: information abstraction and presentation, relaying information to different user levels, and temporal navigation. This dissertation proposes solutions to these three problem areas in Chapter VI.
CHAPTER III

COGNITIVE TASK ANALYSIS RESULTS

Choosing Cognitive Task Analysis Techniques

Conducting a Cognitive Task Analysis (CTA) has been shown to assist in developing and introducing new robotic technology by facilitating an understanding of the domain and the appropriate robot tasks (Adams, 2005; Almirao et al., 2007; Adams et al., 2008). Chapter II discussed three categories of CTA techniques (i.e., Goal-driven, Information-driven, and Crossover) and their respected strengths and weakness. Two CTA techniques were chosen for the analysis of the CBRNE domain to balance their strengths and weakness. The two CTA techniques are Goal-Directed Task Analysis (GDTA) (Endsley et al., 2003) and modified Cognitive Work Analysis (CWA) (Cummings, 2003). The crossover nature and directness of GDTA along with the broad diversity of the CWA methods provide a more specific and insightful CBRNE domain analysis than either method on its own.

There are several others who have used multiple CTA methods to balance the CTA methods strengths and weaknesses (e.g. Adams et al. (2008), Jamieson et al. (2007), Kaber et al. (2006), and Miller & Vicente (2001)). However, only Adams et al. (2008) and Kaber et al. (2006) have paired the GDTA and CWA, as this dissertation does. Kaber et al. (2006) employed both GDTA and CWA’s Work Domain Analysis (WDA) for a
supervisory control interface design in high-throughput organic compound screening operation. Adams et al. (2008) employed both GDTA and two components of CWA’s WDA and CbTA to analyze an existing human-based wilderness search and rescue response. Both Kaber et al. (2006) and Adams et al. (2008) found that the two analysis methods complimented each other and the resulting analysis was more complete and useful than analyses conducted by a single technique.

Miller and Vicente (2001) compared hierarchical task analysis (HTA) with WDA and presented the associated advantages and disadvantages. Their findings hold, with two exceptions, when employing GDTA and WDA to the CBRNE analysis in part because GDTA is structurally similar to HTA as discussed in Chapter II. The first exception is that they concluded that the HTA more easily identified priority, procedural, and temporal constraints than the WDA. In our analysis the inability to easily identify temporal constraints was a limitation of the GDTA, the WDA, and CbTA when done with decision ladders. This led the CBRNE analysis to employ statecharts instead of decision ladders for the CbTA (see Chapter III) and to develop and perform the CIFA (see Chapter IV). Second, Miller and Vicente (2001) felt that the HTA was not as useful as the WDA for identifying information requirements. This finding may be an artifact of the order in which they conducted the analyses: the WDA prior to the HTA. We have found the GDTA more beneficial for identifying information requirements than the WDA; however, this is hardly surprising knowing that one of the GDTA’s focuses is identifying information requirements.

The two chosen CTA techniques used to analysis the CBRNE domain span all three CTA categories as the CWA’s WDA is a Goal-driven CTA, CWA’s Constraint-
based Task Analysis (CbTA) is an Information-driven CTA, and the GDTA is a Crossover CTA. This chapter discusses the GDTA and CWA results, including any changes made to these techniques in applying them to the CBRNE response system.

People as System Components

The CTA presented in this dissertation treats the human responders in the CBRNE response system as system components. There is some precedence for treating people as system components as Adams et al. (2008) conducted CTA with the same perspective. Traditional task analysis views the humans as operators or monitors and the system components as being purely physical (e.g. water tank, missile). The human responders in the CBRNE response system and their associated tasks and activities are more akin to elements in the system rather than operators or monitors of the system. In the CBRNE response system, it became essential to view human responders (e.g. a HazMAT team) as system component. Viewing human responders as system components is essential because the CBRNE response system is almost entirely comprised of human responders unlike, for example, a chemical plant that has a physical system. However, this perspective does not mean that all people are treated as system components. Just as it is with the chemical plant, there are individuals who direct the CBRNE response system and are, therefore, not viewed as system components.

Methodology

The GDTA and CWA results have been developed over three years and the models presented in this chapter and in the appendix represent many hours of research. A
preliminary CBRNE response system analysis was constructed using GDTA and CWA based on a collection of documents relating to CBRNE or incident management (Coast Guard, 2006; District 5, 2005; FEMA, n.d.; Shane, 2005; Office for Domestic Preparedness, 2003; US Army Corps of Engineers, n.d.; Howe, 2004, 2005; Homeland Security, n.d.; FEMA, 2005; LaTourrette, Chan, Brower, Medby, & McMahon, 2006; NDOJ, 2005; Peterson, 2002; Ridge, 2003a, 2003b). Subject matter experts included members of the Nashville bomb squad, law enforcement, HAZMAT, SWAT, incident command, fire department, public health, Emergency Medical Services (EMS); Tennessee Bureau of Investigation; The Nashville Mayor’s Office of Emergency Management (OEM); the local FBI field office; and the 45th Weapons of Mass Destruction Civil Support Team.

The GDTA model was constructed first and its development always preceded the development of the CWA. The initial GDTA was based on the document review and was repeatedly presented to subject matter experts and revised. An initial WDA was subsequently presented to a few subject matter experts; however, the WDA was much more difficult to communicate to the subject matter experts and resulted in very poor feedback in comparison to the GDTA. Therefore, in addition to the interviews regarding the WDA, the feedback from the GDTA and the interviews in general drove both the GDTA and the CWA development. The more refined the GDTA became the more refined the CWA became.

After the first rounds of document review, interviews, GDTA and CWA development, and subject matter expert review, several exercises were witnessed. Tabletop exercises focusing on chemical CBRNE incidents were attended in Knoxville,
TN and Franklin, TN. Several full scale exercises conducted by the 45th Weapons of Mass Destruction Civil Support Team stationed in Smyrna, TN were observed. A large scale multiple day full-scale exercise conducted by the Greater Nashville Homeland Security District 5 was also observed in 2005. These exercises provided new insight into the CBRNE response system and motivated many changes in both GDTA and CWA as well as another round of subject matter expert interviews.

A scenario was adapted from the Greater Nashville Homeland Security District 5 2005 exercise to facilitate another round of subject matter expert interviews for analysis validation purposes. The scenario provided an example incident that allowed the subject matter experts to respond and discuss their insights in a more structured but natural manner than general interviews and GDTA reviews. Using an example to connect to subject matter experts is a well-established procedure that yields good results (Wickens et al., 2003). The review of the scenario provided the last round of subject matter expert reviews.

The entire scenario text was then extended to represent how, hypothetically, robots can be employed and what contributions those robots can provide. This scenario is included in its entirety in Appendix D. A short excerpt from the original scenario text is presented to facilitate a discussion of the GDTA and CWA results. The GDTA and CWA results are then subsequently presented followed by the same short excerpt scenario, but this time with robots and the robots’ hypothetical contributions.
The Emergency Evaluation Example

The CBRNE response system encompasses many government agencies, organizations, and responsibilities. The first pass analysis represented the entire response and later efforts focused on areas identified as most appropriate for potential robotic technology. Presenting the entire CTA results in this chapter would be tedious; therefore, this chapter focuses on a particular subset of the CBRNE response system when discussing the detailed results of the CTA techniques. The complete CTA results are provided in Appendix A and Appendix B. The presented example is based on the CBRNE domain responsibility of Emergency Evaluation. The following scenario text is taken from the Greater Nashville Homeland Security District 5 2005 Emergency Preparedness Challenge Exercise: Controller/Evaluator Handbook (District 5, 2005) and it provides an example of the emergency evaluation activities without robots.

At 1:00pm, the TN Tower (State Building) explodes.

At 1:01pm, multiple 911 calls are received in the Emergency Communications Center reporting explosions at the TN Tower building. Some calls report that the TN Tower was bombed.

At 1:03pm, building security personnel are reporting massive amounts of casualties and fatalities on scene.

At 1:05pm, First Responders begin to arrive at the scene and report there has been an explosion at the TN Tower. The west side of the TN Tower has been torn off and has collapsed into the building about 150 feet wide and 100 feet into the building and upwards of approximately 300 feet. Several small fires and a damaged portion of the TN Tower have been reported. People are walking around dazed, confused, and bleeding. There are bodies and body parts visible lying on the ground. The debris in the street is slowing down responders.

At 1:07pm, The ECC’s Field Incident Response Situation Team (FIRST) deploys to the scene and takes over all tasks normally handled within the center, including notifications and requests for additional resources. The ECC begins to backfill fire halls and perform medical move ups to provide
coverage for the remainder of the City. The MCI plan is activated and notifications are made.

At 1:08 pm, Additional First responders arrive on scene to find many Good Samaritans are on the collapsed structure trying to help. Good Samaritans are knocking over debris and falling down while walking and shifting the debris. (District 5, 2005)

This scenario appears to be a bomb incident and it is in these early moments when the Emergency Evaluation activities begin. The goal of the Emergency Evaluation activities is to assess the hazards so that the rest of the CBRNE response system understands the nature of the threats and the system can respond and perform its other responsibilities appropriately. This is exactly what starts happening at 1:05pm in the scenario. That paragraph states that the First Responders began to arrive and then immediately started reporting the nature of the hazards at the scene.

Goal-Directed Task Analysis

Methodology

The GDTA technique, in practice, has four primary stages: development of a goal hierarchy, conducting interviews, developing the expanded goal-decision-SA structure, and obtaining feedback. The goal hierarchy is a visual structure defining the primary and secondary system goals. Its development includes an exhaustive document review, personal contact, free-flowing interviews with subject matter experts, and observation of the current system. Structured interviews with subject matter experts were conducted in order to confirm and modify the initial goal hierarchy. Once the interview results were incorporated into the goal hierarchy, the expanded goal-decision-SA structures were
developed by adding additional sub-goal levels in order to obtain the desired detail level. Extensive feedback from subject matter experts regarding SA requirements refined the GDTA into a meaningful sketch of the CBRNE domain with an acute focus on the information required to make ideal decisions.

Goal Hierarchy

The first step in analyzing the CBRNE response system was to review literature, manuals, procedural documents, and reports regarding the system’s operation. The primary document source was the Department of Homeland Security. A division of tasks/goals was found in the Planning Scenarios Executive Summaries (Howe, 2004, 2005). The document provided a means to divide high-level tasks into different categories, each with a primary goal that was a logical starting point for the goal hierarchy.

Additional scenarios and other related documents were employed to develop the preliminary goal hierarchy and preliminary SA requirements (Coast Guard, 2006; District 5, 2005; FEMA, n.d.; Shane, 2005; Office for Domestic Preparedness, 2003; US Army Corps of Engineers, n.d.; FEMA, 2005; Homeland Security, n.d.). After several subject matter expert interview and revision cycles, the post-interview goal hierarchy was finalized (Figure 10).

The goal hierarchy, Figure 10, begins with the main CBRNE response goal of “Life Safety, Incident Stabilization, and Property Conservation,” which is the concatenation of the three overarching goals of the CBRNE response system, as
discussed in Chapter II. The next level goals are: “Prevention/Deterrence,” “Emergency Evaluation,” “Emergency Management,” “Incident/Hazard Mitigation,” “Victim Care,” “Public Protection,” “Investigation/Apprehension,” and “Recovery/Remediation.” These goals are further decomposed into tasks and information requirements.

Figure 10: The resulting subject matter expert approved GDTA goal hierarchy.

Goal Hierarchy Goal Ordering

The horizontal ordering of the goals does not traditionally represent chronological order in the GDTA; however, a horizontal time ordering from left to right was loosely applied in this dissertation in order to better convey the relationship between the goals. The subject matter experts provided feedback regarding the timing of the goals and suggested that the goals be chronologically ordered. Figure 11 presents this ordering and the duration of the top-level goals in basic terms (i.e., no event, pre-event, event start, first minutes, first hours, days, and months.) Figure 11 was presented along with the
preliminary goal hierarchy to facilitate communication with the subject matter experts during interviews.

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![Figure 11: GDTA Goal Hierarchy top-level goal timeline.](image-url)

Expanded goal-decision-SA structure

After the first complete review of the goal hierarchy with the subject matter experts, the expanded goal-decision-SA structures for the lowest level goals were developed. The expanded goal-decision-SA structures’ purpose is to understand the SA requirements of the lowest level goals. Creation of the expanded goal-decision-SA structures are achieved by extensive subject matter expert review and through witnessing the system in action. The initial review focused on capturing decision questions and their related SA requirements. The subject matter expert feedback method was structured employing forms containing specific questions to determine the relevance of and the relationship between the goal, its general decision question, and its associated SA requirements.
Once each relevant decision question was accurately established, the focus became that of identifying the SA information requirements. The information requirements upon completion of the first review were incomplete and unspecific; therefore, sub-sub-goals were added in order to increase the granularity of the SA information requirements. Figure 12 provides four sub-sub goals for the sub-goal 2.0 Emergency Evaluation where each sub-sub goal also has an associated decision question.

**Figure 12: GDTA Sub-sub goals from sub goal 2.0 Emergency Evaluation.**

The first SA information requirements revision asked the subject matter experts to provide feedback on a single list of proposed information requirements, see Figure 13. The vague questioning resulted in a review that was shallow and incomplete. Four categories were introduced to capture more of the information being provided by the subject matter experts and to facilitate more thorough discussions. These four categories are tools and resources, thought processes, people and groups, and information requirements. The purpose was to facilitate a clearer and more complete SA requirements review for each sub-sub-goal. The tools and resources are those objects that provide
information used in SA perception and comprehension. Thought processes are mental notes or tasks that contribute to the comprehension and projection elements of SA. The people and groups, while not strictly an SA information requirement, assisted in identifying who was involved with a GDTA goal. The fourth category, information requirements, became the list of information items there are used to establish SA and accomplish the goal. A new form was created to effectively structure the subject matter expert responses in reviewing the proposed expanded structure and corresponding situational requirements; this form is partially shown in Figure 14.
Goal 2.1

Does the question below the box capture the general decision to be made in relation to this goal?

Yes □ No □ if not, why? AnswerHere

Are there other questions that would be appropriate? If so, please provide them. AnswerHere

Review the items in the bulleted list below the question. What changes or additional information is needed to achieve this goal that should be included? AnswerHere

**Figure 13: Simple SA structure review form along with an early version of the GDTA.**
The categorized form results encompassed a more thorough and complete SA information requirements snapshot, as is evident in Figure 15. The expanded goal-decision-SA structure in Figure 15 is not the standard GDTA structure but reflects the need to capture the additional necessary information. The modified SA requirement blocks are distributed among the sub-sub-goals in order to improve the relationship between SA requirements and the associated lowest level goals. Without categorizing the SA requirements, the feedback regarding the involved people and groups was minimal.

Figure 14: Expanded goal-decision-SA structure review form.
2.3 On Scene Health and Hazard Assessment

2.3.3 Assessment

How can representative samples be gathered?

What type of hazard has been detected?

How can changes in the emergency situation be anticipated and preempted?

Tools and Resources

- Computer programs, i.e., Cobra 4.0
- Thought Processes
- Updating of maps for stability
- Robotics
- Archival data that allow quick retrieval and subsequent analysis, investigation, and official reports
- Robotics
- Identification of possible protective action recommendations (PARs) to the public

Information Requirements

- Guidance from Incident Commander
- Availability of communication systems
- Meteorological monitoring system
- Knowledge of plans and procedures
- Event significance (political, sports, etc.)
- Structural integrity
- Knowledge of plans and procedures
- Metronomy, epidemiology, lab results, reports from hospitals, clinics, local public health departments

Image Requirements

- Guidance from Incident Commander
- Availability of communication systems
- Availability of maps for stability
- Result from 2.3.3 Collect hazard information
- Result from 2.3.5 Situation status report
- Result from 4.2.2 Protective action guides
- Result from 4.2.2 Protective action guides
- Disease time factors (time between when symptoms appear and death)

Figure 15: The modified GDTA Expanded goal-decision-SA structure for the sub-sub goals of sub-goal 2.3 On Scene Health and Hazard Assessment.
Numbering Information Requirements

The information requirements listed in the expanded goal-decision-SA structure have an additional feature not found in a standard GDTA. Each information requirement has been assigned a unique number (e.g. 0031). The unique number helps to establish where two or more information requirements, despite possibly slight wording differences, represent the same information requirements.

This feature was added to assist with combing the GDTA and CWA results into the Cognitive Information Flow Analysis (discussed in Chapter V). For example, the GDTA information requirement “Reports describing the incident (Initial and periodic)” is number 0045 and is part of GDTA goal 2.3.3 Assessment and is correlated with CWA’s WDA object “Incident Reports” which is labeled as object “h” in Figure 19.

Narrowing the CBRNE Response System Areas

The GDTA identified eight second-level goals that also serve as CBRNE response system areas of focus, as shown in Figure 10. Some of these goals are more applicable for incorporating robots than others and subsequently those goals that were applicable were developed in more detail. The areas where robots were deemed most suitable are based on the results of the GDTA, CWA, and subject matter expert interviews. This is not to imply that robots can not be useful in the other areas, simply that these areas have the potential for the greatest improvement if robots are incorporated. The four areas and
goals that are most suitable for incorporating robots are “Emergency Evaluation,” “Emergency Management,” “Incident/Hazard Mitigation,” and “Victim Care.”

Cognitive Work Analysis

Methodology

The Modified CWA (Cummings, 2003) consists of seven stages: analysis of global social, organizational, and ethical factors; Work Domain Analysis (WDA); Constraint-based Task Analysis (CbTA); the creation of a simulated domain; analysis of effective strategies; analysis of social and organizational factors; and identifying demands on worker competencies (Figure 1). The Modified CWA begins by understanding the environment in which the system is used through the analysis of global social, organizational, and ethical factors and a WDA. As the environment is understood, the analysis transitions its focus from ecological elements to a cognitive analysis that accounts for the user’s actions.

Since this dissertation’s focus is on the development of a system of human-robot interfaces for use with novel robotic systems in the CBRNE response system, only the first four steps of modified CWA are being used. The last three steps are will be address partly through user testing (see Chapter VII). This chapter presents the CBRNE response system results for the analysis of global social, organization, and ethical factors, WDA, and CbTA. The initial simulated domain results from the pilot study are discussed in Chapter VII.
Analysis of global social, organizational, and ethical factors

The analysis of global social, organizational, and ethical factors is designed to foster safer, more effective development of novel technology (Cummings, 2003). The analysis increases the designer’s development of a “moral imagination” and an ethical mental model as this system has the ability to affect the welfare and safety of the public (Gorman et al., 1999). This analysis has three elements that are presented in the next three sub-sections: ethical factors, relevant social groups, and communication flow map.

Ethical Factors

The CBRNE response system equipment is currently predominately manual in nature, meaning that there is very limited use of information technology. The system’s manual nature implies that the introduction of smart tools and robotic systems will be sensitive both ethically and socially. The greatest ethical factor put forth by Cummings (2003) is accountability, or who is responsible for mistakes that happen with the new system. Accountability cannot be overlooked, as any introduction of systems that support decision-making will be partly responsible for the success or failure of those decision outcomes. What makes the introduction of technology daunting is that these decisions usually directly affect the lives of individuals in the local environment as well as those in the interconnected global environment. Social tensions must be taken into account and eased. Therefore, the robotic systems must be presented as effective and reliable tools, not as human replacements, which they are not intended to be. Tools must be effective.
and reliable to establish user trust and increase adaptation and acceptance (Sheridan, 2002). Designing, developing, and testing new CBRNE technology will be insufficient to address the ethical and social issue without implementing a corresponding plan for incorporation, training, and failure detection. Without this plan and a focus on accountability, the technology will face difficult and incomplete acceptance in this very human-centric domain. This plan will be developed in parallel to the development and implementation of the proposed CBRNE robotic system and is left to be completed after the proposal.

Relevant Social Groups

Cummings (2003) expresses social factors through identifying the relevant social groups involved with the system being analyzed. One of the focuses of the relevant social groups is to identify both stakeholders and those who will in some way be affected by the new system. A combination of documents (District 5, 2005; FEMA, n.d.; Howe, 2004, 2005; Office for Domestic Preparedness, 2003; Shane, 2005), subject matter expert interviews, and exercise observations were used to construct the relevant social group map (Figure 16). The CBRNE response system is a human-centric system with many people and organizations that are involved at some level; therefore, the relevant social group map displays 56 different individuals and organizations. The map groups the individuals and organizations roughly by type with local individuals and groups being displayed on the top and right sides and the federal groups displayed along the bottom and left sides. The sheer number of individuals and groups potentially involved in a
CBRNE response provides a glimpse into why the CBRNE incident response is so complex.

Figure 16: The CWA Relevant Social Groups of the CBRNE response system.
Cummings (2003) introduces Communication Flow Maps into the CWA as the step following the identification of relevant social groups. The goal of the Communication Flow Map is to illustrate how the different social groups communicate with each other and consequently how information is passed throughout the system. The CBRNE response Communication Flow Map is presented in Figure 17 in a simplified and more readable version. The full version is presented in Appendix B. The CBRNE response system Communication Flow Map does not explicitly depict all the groups identified in the relevant social groups map. The groups that interact with the Joint Operation Center and the Joint Information Center or the Public Information Officer only are not depicted, as their impact on the robotic system will be minimal and their inclusion would simply add undue complication and clutter to the Communication Flow Map. The lines in the Communication Flow Map represent direct and authorized communication interactions; however, in practice, according to the subject matter experts, communication occurs outside of these specific connections due to personal relationships. For example, the Unified Command and a Law Enforcement agent may be good friends and they may communicate directly, although organizationally they do not communicate directly.
Figure 17: The simplified CWA Communication Flow Map of the CBRNE response system.

Work Domain Analysis

The WDA focuses on understanding the relationships between subsystems and components and is often graphically represented as an abstraction decomposition table (J. Rasmussen, 1985). We began our WDA with a review of the literature, manuals, procedural documents, and reports regarding the system’s operations in order to discover the subsystems of the CBRNE domain (Coast Guard, 2006; District 5, 2005; FEMA, n.d.; Shane, 2005; Office for Domestic Preparedness, 2003; US Army Corps of Engineers, n.d.; Howe, 2004, 2005). The Homeland Security Planning Scenarios Executive Summaries (Howe, 2004), subject matter expert interviews, observed exercises, and preliminary GDTA results provided the means to divide the overall CBRNE response system into different categories and sub-systems as defined in Figure 18. Figure 18 depicts three categories: Management Response System, Health Response System, and
Hazard Responses system. These three categories are abstract functions of the overall goal of “Life Safety, Incident Stabilization, and Property Conservation.” The three categories are comprised of eight sub-systems (Figure 18).

<table>
<thead>
<tr>
<th>CBRNE Response System</th>
<th>Categories</th>
<th>Sub-Systems</th>
</tr>
</thead>
<tbody>
<tr>
<td>Goal</td>
<td>Life Safety, Incident Stabilization, and Property Conservation</td>
<td></td>
</tr>
<tr>
<td>Abstract Functions</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Goal</td>
<td>Life Safety, Incident Stabilization, and Property Conservation</td>
<td></td>
</tr>
<tr>
<td>General Functions</td>
<td>Management Response System</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Policy &amp; Administrative Management (OEM)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Command Management (IC)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Health Response System</td>
<td></td>
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<tr>
<td></td>
<td>Public Protection</td>
<td></td>
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<tr>
<td></td>
<td>Victim Care</td>
<td></td>
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<tr>
<td></td>
<td>Hazard Response System</td>
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<tr>
<td></td>
<td>Emergency Evaluation</td>
<td></td>
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<tr>
<td></td>
<td>Incident/Hazard Mitigation</td>
<td></td>
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<tr>
<td></td>
<td>Recovery</td>
<td></td>
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<tr>
<td></td>
<td>Investigation/Arrehension</td>
<td></td>
</tr>
</tbody>
</table>

Figure 18: The Work Domain Analysis of the CBRNE response system, top levels only. The abstraction functions that have a bold border are the ones relevant to robotic systems.

After identifying the system’s categories and subsystems, the next step is to identify the priority measures, general functions, processes, and objects that belong to those subsystems. The Emergency Evaluation subsystem WDA is presented in Figure 19 and has been reviewed and validated by subject matter experts.

The Emergency Evaluation system WDA has two sub-systems: Life Safety Assessment and Victim Status and Awareness. The Victim Status and Awareness overlaps with the Victim Care system and, therefore, is continued in that WDA, presented in Appendix B. The Life Safety Assessment contains four general functions: Hazard
Identification, Collect Data, Simulation, and Archive Data. These general functions are then broken into functional units, which are linked to processes. These general functions and processes are associated with a number of object components, which represent the tools and physical objects used during Emergency Evaluation. Throughout the WDA, letters (e.g. “a”)) have been added to the node names. These letters were added to provide a means of uniquely identifying individual nodes in conjunction with a row and column number. For example the node “Hazard Assessment” in Figure 19 is uniquely identified as 2.3.a meaning it is in the 2 row and 3 column with an “a)” before its name.
Figure 19: The WDA of the Emergency Evaluation subsystem.
Constraint-base Task Analysis

Whereas the WDA yields information regarding environmental constraints and provides an overall system perspective, the CbTA delves deeper and focuses on the action items, information, and relationships that are considered in the decision-making process (Vicente, 1999). The next two sections present the traditional method of representing a CbTA analysis and the method employed in this dissertation.

Decision Ladders

A CbTA is often visually represented as a decision ladder (J. Rasmussen, 1988), which is based on a two-step action-knowledge structure. The actions are linked together in an action-means-end relationship (Vicente, 1999). A decision ladder for Emergency Evaluation is provided in Figure 20, which represents knowledge states as oval shapes, action or information processing states as rectangle shapes, and the lines representing the paths between states. The paths in Figure 20 are all regular paths or struts as there are no leaps represented. The decision ladder is constructed based on careful analysis of the information provided in Figure 19 and from the literature review, subject matter expert interviews, and exercise observations. One of the most interesting discoveries in Figure 20 was the presence of three loops, all returning to the collecting environmental samples activity. The smallest loop provides information regarding how dangerous the environment is to the responders. The second loop, which only occurs after the first loop, provides information concerning how safe the physical environment is for the responders. The third loop is the primary loop as the search action is performed. The return of the
search loop implies that if the conditions of either of the other two loops changes, this loop will not repeat until the situation is reassessed as relatively safe. Figure 20 clearly shows the hierarchy of needs: the search occurs only if the structure is relatively stable and the assessment of the structure only occurs if the environment is relatively safe.

Figure 20: The CbTA Decision Ladder for Emergency Evaluation.
The CbTA is traditionally represented with Decision Ladders (Vicente, 1999) which are based on Finite State Machines. However, when a Decision Ladder involves more than one decision sequence or the decisions overlap in time, the Finite State Machine model is inadequate, as it cannot represent concurrency and decisions succinctly. Multiple decision sequences, timing, and hierarchical relationships are a characteristic of team-based domains. Capturing these constraints is paramount to understanding the team decision-making process (Gonzalez, 2004). Therefore, Statecharts are proposed as an alternative to Decision Ladders because Statecharts can represent decision concurrency and hierarchical relationships succinctly. Statecharts (Harel, 1987) are a software engineering tool that has been applied to human-computer interaction (Loer & Harrison, 2003). Statecharts have similar expressive power as the Hierarchical Task Analysis (HTA) (Shepherd, 2000), discussed in Chapter II; however, HTA can represent an entire domain while the CbTA focuses on a particular task.

Figure 20 provides a Decision Ladder for the CBRNE response system sub-system Emergency Evaluation, while Figure 21 provides the corresponding Statechart approach. The Decision Ladder approach does not clearly represent that all presented decisions occur only when it is safe to do so. This element is easily expressed in the Statechart via the embedded hierarchy (i.e., the elements inside another element can only occur if the parent element is the current state). Furthermore, the Decision Ladder has difficulty representing the concurrent activities, as it must enumerate all combinations of active tasks. For example, a simultaneous evaluation of the environment and structural integrity is required prior to entry and continues during the victim search. If dangerous
conditions arise, the rescue personnel abandon the victim search and seek safety. These concurrent and hierarchical relationships inherent in the Emergency Evaluation task cannot be represented in a Decision Ladder without an excessively large number of states.
Figure 21: The CbTA State-chart version of Emergency Evaluation.
The use of Statecharts over Decision Ladders in the CWA has proven better in capturing complex team-based decision-making. The ability to capture the hierarchical and concurrent aspects of decisions is essential as they directly affect decision-making.

The Emergency Evaluation Example with Robots

At the beginning of this chapter, an emergency evaluation example was presented as it is currently conducted without robots. After conducting the GDTA and CWA analyses, the entire scenario text was modified to include robots and how they may assist with and alter the CBRNE response system (see Appendix D). The following example is a small excerpt from the modified scenario text that corresponds with the original scenario text presented earlier in this chapter and represents how robots may alter the incident response.

At 1:05pm, First Responders begin to arrive at the scene and immediately deploy robots for detection, identification, and scene tracking. The responders and the robots report that there has been an explosion at the TN Tower. Using the robots, the responders report that the west side of the TN Tower has been torn off and has collapsed into the building about 150 feet wide and 100 feet into the building and upwards of approximately 300 feet and that several small fires and a damaged portion of the TN Tower have been reported. The aerial robots indicate that people are walking around dazed, confused, and bleeding. Those that are victims start being assessed by medical initial assessment configured robots. Those victims that can be transported away are starting to be moved away via the medical victim transportation configured robots. There are bodies and body parts visible lying on the ground. The debris in the street is slowing down responders; however, they are using their resource-hauling robot to help them carry their equipment around the debris. A decontamination system, a robotic system is being deployed to thoroughly decontaminate the team from possible exposure to harmful agents.

At 1:08pm, Additional First responders arrive on scene to find many Good Samaritans are on the collapsed structure trying to help. They instruct the
Good Samaritans to limit damaging the debris and deploy aerial robots to recon into the area preventing more Good Samaritans from getting hurt.

The modified scenario text was described to subject matter experts and they found the robot possibilities intriguing and the assistance provided by the robots to be plausible and potentially very useful. The following is a description of how the robots altered and affected the response.

The first change introduced is the rapid deployment of the robots to detect, identify, and track the scene providing a potentially richer initial report and scene assessment. The early assistance in assessing the scene for an initial report is especially useful if the responders must suit up in their personal protective equipment, which is cumbersome, reduces their field of view and maneuverability, and requires up to half an hour to prepare. The second change is that the robots, not the responders, are in the area observing the TN Tower’s damage and civilian and victim activity. Deploying the robots in the area allows the responders to remain at a safer distance, thereby reducing their health risk. The next change in this short example is that the decontamination is performed by a robotic system, ensuring a level of confidence in the decontamination as well as removing the need for the responders to setup the system, a task that they must perform before being able to enter the hazard zone. Setting up the decontamination equipment took over thirty minutes during one sub-scenario observed during a full-scale exercise and those early minutes are critical in saving lives, as was repeatedly expressed by the subject matter experts. The last change is deploying aerial robots to perform reconnaissance of the area. Aerial robots may execute a survey task more quickly than human responders, which may reduce the health risk to Good Samaritans and responders.
Cognitive Task Analysis Summary

The combination of GDTA’s straightforwardness and its focus on SA with the CWA’s broad scope has provided a much more specific and insightful analysis. The results show how the current CBRNE response system is extensively human-centric and how little the humans rely on any form of intelligent systems or equipment. This finding further confirms that incorporating new robotic systems is fundamentally a paradigm shift for the CBRNE response system.

The GDTA provided a workable understanding of the CBRNE response system, whereas the modified CWA captures elements outside the GDTA’s scope, such as the global social, organizational, and ethical factors. However, the subject matter experts more readily identified with the GDTA goals and SA requirements. The GDTA was easier to discuss with and present to the subject matter experts when compared to the CWA’s WDA. The WDA was more difficult to discuss with the SMEs mostly due to its higher learning curve because of its matrix format where two axes each represent a different relationship. In contrast, the GDTA has a single represented relationship. The GDTA also appears more like a standard organizational hierarchy chart, with which the subject matter experts were already familiar. In addition, the GDTA’s goals, tasks, and SA requirements map more cleanly to the existing CBRNE documentation than did the modified CWA components. The subject matter experts found that the GDTA supported their decision-making terminology clearly and succinctly partly due to its focus on SA requirements. The results of the GDTA and the modified CWA provided a means to
identify SA requirements, narrow the CBRNE responds to areas of robotic interest, identify potential robot tasks, formulate user levels, construct the Cognitive Information Flow Analysis, review the impact of potential robot tasks, and inform system design. Greater than the sum of their parts, the combination of the two techniques has been useful in viewing the many facets of the CBRNE response system.
CHAPTER IV

USER LEVELS

The CBRNE response system is a human-centric system that can involve thousands of responders and many thousands of civilians and victims. The CWA Relevant Social Groups diagram in Chapter III (see Figure 16) identified 56 different individuals and organizations that may be involved with the response. The introduction of a new robotic system will affect the workflow, decision-making, and responsibilities of the responders. Each CBRNE event response differs dramatically in scope; therefore, it is impractical to define user roles for each potential responder that may interact directly or indirectly with the robotic system. The individual responders and victims have been abstracted into ten user levels based on the IUCMCI-Student Manual (FEMA, 2005), subject matter expert interviews, and GDTA and CWA results.

The Five Factors

The ten user levels are defined by five factors: the human-robot interaction role (HRI Role), the hazard zone occupied (Zone), the information types provided by the robotic system (Information Type), the user’s responsibilities to the robotic system mission (Responsibilities), and real responder CBRNE roles (Real Roles). These five factors are discussed in the following sections.
HRI Role

The User Level differentiates the type of interaction between the users and the robotic system. The User Level concept is based on the human-robot interaction (HRI) roles defined by Scholtz (2003) and extended by Goodrich and Schultz (2007). This dissertation includes five of the defined interaction roles and adds a new interaction role. The five pre-defined HRI roles are supervisor, operator, peer, information consumer, and bystander. The supervisor role has authority over and manages the other HRI roles and can monitor and review robots. The operator role works “inside” the robot, directing its behaviors and actions either by modifying parameters or through teleoperation. The peer role works alongside the robots, in the same common physical space, towards completing a shared assignment while interacting with the robots as if they were teammates. The bystander role is similar to the peer role in that the person resides in the same common physical space as the robot; however, the bystander does not work intentionally towards some shared assignment or goal. The information consumer does not directly interact with the robots, but rather uses information that originates, at least partially, from the robots.

Abstract Supervisor Role

The new HRI role defined in this dissertation is the abstract supervisor role. The abstract supervisor is an individual who resides above the supervisor in the chain of command and is responsible for a broad set of system components, which includes robots and their operators as well as responders not related to the robots. The abstract supervisor is also a problem holder, that is, an individual who sets the goals and objectives. The
abstract supervisor’s interaction with the robots is partially as an information consumer and partially as a supervisor. The abstract supervisor consumes information that originates with the robots; however, this information is often abstracted in such a way that the abstract supervisor may not realize the information originated from the robots, similar in concept to the information consumer. However, the abstract supervisor, unlike the information consumer, can modify the system response objectives and goals in response to the information reviewed, thereby affecting the tasks the robots are or will be executing, similar to the supervisor role albeit in a more abstract manner.

The following example illustrates the different interaction roles and the complementary interaction between the abstract supervisor, supervisor, and operator user levels. An aerial robot can record a chemical reading as part of its surveillance task of a particular area. The operator completes the surveillance task by successfully navigating the aerial robot. After monitoring the task the supervisor notes two things: the task was successful and the chemical reading needs to be reported to his superior, the abstract supervisor. Upon review of the report, the abstract supervisor realizes that the chemical reading corroborates evidence another agency is reporting and decides that this region should be evacuated. The abstract supervisor issues a new goal to evacuate the area, which then causes the supervisor to direct this operator to change the robot task from surveillance to monitoring and assisting with the evacuation.
The CBRNE personnel function in three hazard zones (Zone): Hot Zone, Warm Zone, and Cold Zone. The Hot Zone is where exposure to the hazard is the most severe, requiring the highest level of personal protective equipment (US EPA, n.d.), as warranted by the particular hazard. The Hot Zone area is determined by the hazard’s area of greatest influence (e.g. a bomb’s explosive radius). The Warm Zone is defined as the area surrounding the Hot Zone and is where that hazard’s danger is present, but at limited levels and is unlikely to result in long-term or lingering damage to one’s health. The Warm Zone starts at the edge of the Hot Zone and continues until the effects of the hazard can no longer be experienced. The Cold Zone is the area surrounding the Warm Zone and is the area in which the effects of the hazard are insignificant, but possibly detectable. The Cold Zone is everywhere outside the Warm Zone. Users are defined by the most dangerous zone to which they are likely to be deployed; however, it is very likely that users will be in less dangerous zones and can be temporarily deployed to a more dangerous zone.

Information Type

The information produced by the robots is abstracted into three basic types and presented to the CBRNE users: Robot External Status, Robot Internal Status, and Sensors. The Robot External Status provides information regarding a robot’s situation in the world (e.g. information regarding whether the robot is still flying or whether it has crashed.) The Robot Internal Status provides information regarding the internal, or non-
visible, functionality of an unmanned vehicle (UV) system, also known as a robotic system (e.g. battery voltage remaining, communications signal strength, or current motor amperage.) The Sensors provide environmental information acquired from a robot’s sensor suite (e.g. chemical sensors, laser range finder, or video.) Each information type is assigned a number representing how abstract the information is as it relates to each user level. The abstraction number is represented by an ordinal scale from 0, indicating no abstraction, to 4, representing the forth level of abstraction. This abstraction number does not imply that a user level cannot obtain the information at a different abstraction level, but that this abstraction level is the user level’s primary representation.

Responsibilities

Each user level has specific responsibilities during the CBRNE incident. These responsibilities were identified by the CTA methods (see Chapter III) and extrapolated to an incident response using robots or unmanned vehicles. These lists of responsibilities are not inclusive, but rather represent the primary goals that each user level is responsible for accomplishing. Listing the responsibilities provides a richer description of each user level and its perspective scope in the CBRNE response system context.

Real Roles

Each user level is associated with existing CBRNE domain human roles, as defined in the Unified Command Structure (Shane, 2005). The user levels are abstracted
from these real CBRNE domain roles according to how the real roles fit into the
domain roles. The abstraction allows this model to be invariant to CBRNE domain role renaming or
differences in incident organization structure due to resources, region, incident scale, and
hazard scope. For example, when the incident is small and involves a single bomb, many
of the CBRNE domain roles will not exist, as they will not be needed.

The CBRNE User Levels

The CBRNE response system abstracts the human responders into ten user levels.
These ten user levels are defined by five factors: HRI Role, Zone, Information Type,
Responsibilities, and Real Roles. Figure 22 provides the ten CBRNE response system
user levels and their corresponding five factors. The robot, or unmanned vehicle, is
included at the bottom of the figure to illustrate how the information flows and changes
as it progresses through the user levels. The ten user levels from bottom to top are
Victims/Civilians, Direct Human Teammate, UV Specialist, Indirect Human Teammates,
Team Leader, Division Chief, Logistics Technical Specialist, Staging Area Manager,
Operations Chief, and Incident/Unified Commander. The arrows connecting information
types at different user levels indicate that the information is transformed, altered, or
passed from one user level to another. For example, the Logistics Technical Specialist
user level’s Robot General Status information type is abstracted from the UV specialist
user level’s Robot External Status and Robot Internal Status information types, thus the
Robot General Status combines two information types and presents the information at a
more abstracted, or less detailed, level, resulting in a higher abstraction number. The following sections describe each user level.
Figure 22: The CBRNE User Levels.
Victims/Civilians

The Victim and Civilian user level represents bystanders (Scholtz, 2003). Victims require rescuing and both victims and civilians are present in the operational theater. Figure 22 indicates that these individuals may be in the Hot Zone. These individuals may observe the UV’s External Status in a raw, non-abstracted form (i.e. abstraction level 0). It is unclear what, if any, effect the information will have on these individuals as they are consumed with self-preservation actions and thoughts. Victims and Civilians have two primary responsibilities: self-preservation and following responder instructions.

Direct Human Teammate

The Direct Human Teammate interacts directly with UVs in a peer-based relationship (Scholtz, 2003) in the incident hot zone. This user is co-located with the UVs and can access an UV’s External Status and possibly an UV’s Internal Status via direct interaction with the UV (e.g. audio, lights, digital panels) or via a communication portal (e.g. PDA, smart phone, etc). Direct Human Teammate responsibilities include effective UV interaction or interaction in a manner to reduce communication errors; problem solving; and maintaining a local situational understanding in order to efficiently and effectively complete assigned tasks. A large pool of CBRNE responder roles may be classified as Direct Human Teammates, as shown in Figure 22.
UV Specialist

The UV Specialist is responsible for initiating and directing the UVs’ decisions. The interaction between this user level and the UVs will vary depending upon the UVs’ capabilities. This user will typically remain in the Warm or Cold Zones and fulfills Scholtz’s (2003) operator role. The UV Specialist receives direct UV information via the Robot External Status and Robot Internal Status and receives indirect UV information via the Navigation Information, which represents a composite of many sensor readings. The UV Specialist is responsible for effectively tasking the UVs and managing their high-level activities via goal/task assignments and direct teleoperation when required. The UV Specialist is expected to have a local situational understanding based on the UV provided information and is responsible for preventing the UV from negatively influencing the CBRNE response system. The UV specialist user level represents a new role in the CBRNE response hierarchy, which may be termed a Technical Specialist or UV Operator (Goodrich et al., 2007).

Indirect Human Teammates

The Indirect Human Teammate user level is comprised of two groups. One group directly interacts with the incident environment (i.e. in the Hot Zone) but interacts indirectly with the UV system, while the other group does support work in the Cold Zone. Both groups interact with the UV system as information consumers (Goodrich & Schultz, 2007) using UV provided information related either to the incident in general or to specific tasks. The responsibilities of the Indirect Human Teammate user level are to
have local situational understanding, conduct problem solving, and complete the assigned task efficiently and effectively as possible. The real CBRNE roles encompassed in this user level are vast, with the predominate roles being Hazardous Material (HAZMat) Task Force Members, Fire Company Crew Members, Urban Search and Rescue (US&R) Strike Team Members, Extrication Team Members, Triage Group Members, Removal Crew Members, Law Task Force Members, Emergency Operation Center (EOC) and Incident Center (IC) Staff, and Civil Support Team Members.

Team Leader

The Team Leader user level represents an onsite coordinator who supervises one or more responder and UV teams and takes the HRI interaction role of supervisor (Scholtz, 2003). This individual may enter the Warm Zone, but through new technology would ideally reside in the Cold Zone. The Team Leader requires abstracted information from the UVs, represented as the level 2 abstraction level in Figure 22. The Location Information is derived from the Navigation Information while both Incident Related Information and Task Related Information are derived from Sensors. Incident Related Information does not directly address the task but is relevant to other aspects of the response, for example, the possible identification of a secondary device in an open field when the current task is that of inspecting a building for structural damage. Team Leaders manage the UV Specialists and formulate tasks for the UVs and the overall mission. The Team Leader user level responsibilities include maintaining a local situational understanding, problems, and completing the assigned task efficiently and effectively.
There are many real CBRNE roles represented by this user level, such as: HAZMat Task Force Leader, Fire Company Crew Leader, US&R Strike Team Leader, Extrication Team Leader, Triage Group Leader, Removal Crew Leader, Law Task Force Leader, and Civil Support Team Leader.

Abstract Supervisors

Each of the remaining five user levels are fulfilled by individuals who remain in the Cold Zone and are considered abstract supervisors. As the user levels approach the apex of the CBRNE command hierarchy, the number of individuals who fulfill these roles decreases.

Division Chief

The Division Chief user level oversees the activities of several Team Leaders and requires Task Salient Information that can be derived from the Location information and Task Related Information. Task Salient Information highlights and presents the most relevant aspects of the Task Related Information correlated with location. Such information for a structural assessment task may include the number of broken structural beams, number of stable walls, and status of gas and electrical lines. The Task Salient Information may include the status and location of the gas and electrical lines, which may inform other goals such as identifying a means to shut off leaking gas. The Division Chief reviews UV derived information and affects an appropriate response to the derived
information. The Division Chief’s CBRNE responsibilities include effective leadership over the Team Leaders, overall completion of tasks assigned to Team Leaders, and situational understanding. The real CBRNE roles represented by this user level are HAZMat Chief, Fire Branch Chief, US&R Branch Chief, Extrication Group Chief, Medical Branch Chief, Public Works Chief, Law Enforcement Chief, and Civil Support Team Chief.

**Logistics Technical Specialist**

The Logistics Technical Specialist user level manages the resource allocation in a particular operational area. This individual is interested in the UVs’ General Status, which essentially summarizes a robot’s ability to perform a task successfully from a mechanical perspective. This information facilitates the ability to allocate resources appropriately based on need and potential equipment failures. If a UV is about to fail, the Logistics Technical Specialist can procure a backup. Essentially, this individual provides the necessary resources to effectively execute CBRNE tasks, including UV missions. The associated responsibilities of this user level include effective resource management of technical equipment and situational understanding. The Logistics Technical Specialist user level is representative of real CBRNE roles such as the US&R Logistics Technical Specialist.
**Staging Area Manager**

The Staging Area Manager user level oversees the areas where new responders, or augmenters, gather before receiving role and task assignments. The Staging Area Manager requires the Robot General Status and Location Information, which are abstracted to higher level presentations providing key features specific to personnel and equipment placement management. The combination of Robot General Status and Location Information provides the ability to determine where new UV equipment should be deployed for effective utilization, along with the personnel required to accompany or operate the UVs. The responsibilities of this user level are personnel and equipment placement management and situational understanding. The real CBRNE role represented in this user level carries the same name, the Staging Area Manager.

**Operations Chief**

The Operations Chief user level manages several Division Chiefs in order to fulfill the duties of a particular operational area. This user level requires Incident Salient Information which highlights the most important elements within the Incident Related Information correlated with Location Information. For example, Incident Related Information gathered during a structural assessment task may include the identification of a secondary explosive in a nearby field, unidentified chemical residue on an internal building wall, or discovery of an out of place, yet relevant, old newspaper. Incident salient information may include the unidentified chemical residue, which can be used to spawn a new mission to recover and identify the chemical compound, perhaps resulting
in the modification of the overall response. The Operations Chief user level responsibilities include effective leadership, effective operations control, and situational understanding. The real CBRNE roles corresponding to this user level are the Civil Support Team Chief and Operations Section Chief.

*Incident/Unified Commander*

The Incident/Unified Commander user level resides at the top of the response leadership hierarchy and this individual can oversee several Operation Chiefs. The Incident/Unified Commander guides the overall CBRNE response and represents the real CBRNE role of the same name, that is, the Incident/Unified Commander. This user level is focused on Incident salient information, which is at a higher abstraction level than the information presented to the Operations Chief. For example, the Operations Chief may receive information regarding an unidentified chemical residue located in a building. If, once identified, the chemical is determined to be significant (e.g. a nerve agent) then the information is communicated to the Incident/Unified Commander. However, if the substance is identified as benign, such as baking flour, the information may not be communicated to the Incident/Unified Commander. The Incident/Unified Commander’s responsibilities are to provide effective leadership, effective control, and incident understanding for the overall incident response.
Summary

The overall importance of partitioning the CBRNE response system into ten user levels is one part practical and one part design. The practical importance is that the CBRNE response can involve thousands of responders, civilians, and victims with at least 56 different affiliations; therefore, abstraction of the system users into ten levels makes understanding the users more tractable. The design importance is that the user level, especially by identifying the information type needs, assists in developing a system of interfaces for interacting with the proposed robotic system. The defined user levels are directly employed in the Cognitive Information Flow Analysis (discussed in Chapter V) to represent which responders interact with each function that processes and produces system related information. For the remainder of this proposal, interface design will be focused on only two user levels: UV Specialist and Operational Chief. Designing interfaces for the other eight user levels will be left for future work.
CHAPTER V

COGNITIVE INFORMATION FLOW ANALYSIS

Defining Cognitive Information Flow Analysis

Cognitive Information Flow Analysis (CIFA) is a new technique that was developed for this research as a method to integrate and bridge the GDTA and CWA results and the implementation of the proposed system. Unlike GDTA or CWA, the focus of the CIFA is the path of information through the system, both how the information is used and how it is transformed, thereby assisting in the development and integration of new systems.

This chapter starts with the motivation behind the creation of the CIFA, and then discusses the components of the CIFA and the inspiration for those components. The CIFA results, as applied to part of the CBRNE response system, are subsequently presented. The remainder of the CIFA results can be found in Appendix C. This chapter then compares the CIFA results with the GDTA and CWA results, followed by a discussion of the CIFA advantages and concludes with a summary.
Addressing CTA Issues

Three categories of Cognitive Task Analysis (CTA) techniques were reviewed in Chapter II concerning their ability to express the interconnectivity of the various subcomponents; express partial ordering of these subcomponents; and to serve as a guide for developing the command and control of semi-revolutionary systems. The CBRNE response system has been analyzed using the GDTA and CWA methods, which encompass all three categories: Goal-driven, Information-driven, and crossover CTA techniques (see Chapter III for GDTA and CWA results).

After the CWA and GDTA were completed, the CIFA technique was applied to the analyses results. The CIFA technique, therefore, is not in itself a CTA technique, but rather it uses the CTA results as its starting point. It may be possible to perform the CIFA technique without first conducting the CWA or GDTA; however, that proof is left as future work. This sub-section addresses the issues presented in each of the three task analysis categories.

Goal-driven CTA techniques focus on goals, tasks, and functions, making these techniques easy to understand, thereby facilitating communication with subject matter experts and designers unfamiliar with CTA techniques. However, Goal-driven CTA techniques provide limited mechanisms for partial scheduling or representing parallelism, both of which are of interest in the CBRNE response system. One of the goals in choosing a CTA technique is to assist the designers in developing robotic systems to improve the response. These robotic systems will operate in parallel with the existing CBRNE response and will require an understanding of task and information scheduling.
Furthermore, it is likely that the robots will be used as information providers; therefore, explicit representation of the information, its flow, and its effect on the CBRNE response is necessary in order to understand the impact and the benefit the robotic system will provide. It is for these reasons that Goal-driven CTA techniques, by themselves, are not recommended for informing the HRI system design for this domain.

Information-driven CTA techniques were designed to represent the path of information through the system. The two reviewed techniques, CbTA and Visual Dataflow, also allow partial scheduling and representation of parallelism both of which are of interest in the CBRNE response system. These aforementioned CTA attributes present in Information-driven CTA techniques address the outstanding issues with the Goal-driven CTA techniques; however, Information-driven CTA techniques introduce their own disadvantages. The disadvantages of Information-driven CTA techniques are that they deemphasize or ignore goals and they do not directly represent the decision question(s) that form the motivation for tasks.

Crossover CTA techniques are hybrids that combine elements from Goal-driven and Information-driven CTA techniques. The Crossover CTA technique reviewed was the GDTA technique. The GDTA is a Goal-driven CTA technique that incorporates information elements via information requirements. These information requirements can be modeled according to different abstraction levels, which can incorporate full dataflow language modeling. As discussed in Chapter II, this approach, proposed by Flach et al. (2004), is really two modeling methods that are loosely coupled. However, the GDTA is primarily a Goal-driven CTA technique and when used for the CBRNE response system
it became clear that the aforementioned crossover features do not fully mitigate the scheduling and parallelism issues GDTA inherits from Goal-driven CTA.

The issues with the discussed CTA techniques motivated the creation of a new analysis technique that was applied to the GDGA and some of the CWA results (see Chapter III for an overview of the analyses results). The proposed technique is termed Cognitive Information Flow Analysis (CIFA). The CIFA technique is based on the Visual Dataflow technique with a few new features, some of which are borrowed from the GDGA technique. The following sections discuss the components of this new technique, the results of performing the CIFA on the CBRNE example from Chapter III, how the GDGA and CWA techniques compare with the CIFA technique, and the advantages provided by the CIFA technique.

Cognitive Information Flow Analysis Components

CIFA Similarities to Visual Dataflow

The Cognitive Information Flow Analysis (CIFA) technique is based on the Visual Dataflow languages. Like Visual Dataflow, the CIFA is a directed graph with nodes and arcs that connect these nodes (Dennis & Misunas, 1974). The nodes represent functions that consume information from the incoming arcs; produce new information by transforming, altering, or annotating the consumed information; and distribute the new information onto the outgoing arcs (Figure 23). The CIFA function node, like the Visual Dataflow function node as discussed in Chapter II, is represented by a rectangle with rounded corners. The information passed along the arcs is represented by traditional...
rectangles (i.e. squared corners). The relationship between the nodes is that of producer-consumer, as it is in Visual Dataflow. The similarities between Visual Dataflow languages and the CIFA are limited to those discussed above.

![Diagram](image)

**Figure 23: The components of a basic function node.**

CIFA New Features

There are three major differences between Visual Dataflow and the CIFA: two modifications to the function node and one change to the linking arcs. The Visual Dataflow function nodes lack an explanation of purpose as the function nodes only express the action and not the reasons motivating the action or purpose. The GDTA provides an explanation of purpose very elegantly by including a decision question with each function (Endsley et al., 2003), which is designed to capture the question of why this function is performed (see Figure 9). The GDTA decision question feature is included in the CIFA and is added to the function node, as shown in Figure 24. A decision question provides a function node with a goal, or purpose, thereby allowing designers to more freely modify the function’s implementation while still ensuring that its purpose is
achieved. Since one of the purposes of this research is to extend the CBRNE response system by introducing new robotic technology, decision questions are useful necessary component. The new robotic technology will change or add new information items and the inclusion of the decision questions allow designers to determine if the resulting new function compositions adhere to their original purpose as captured in the GDTA decision question.

![Diagram](image)

**Figure 24: CIFA function node with GDTA style decision question added.**

The CIFA technique adds another new feature not present in the techniques previously discussed. This new feature is that of users or user levels associated with a particular function. Most CTA techniques do not explicitly state what user or user level is responsible for a particular function because most analyses and techniques are designed for a single user. However, the information regarding who is responsible for which functions is very important for human-based systems such as the CBRNE response system. The CBRNE response system has hundreds, if not thousands, of active users; therefore, the CIFA specifies user levels rather than individual users. This feature assists with designing the human-robot interfaces for use by the different user levels, as different users have different information requirements, responsibilities, and system interaction styles. The user level feature in the CIFA allows the analysis to specify which functions and information items are important for a particular user or user type, thereby facilitating
the designer’s ability to tailor the interaction with the system to this particular user or user level.

The addition of user or user level information is achieved by adding another box to the side of the function nodes, as shown in Figure 25. The function nodes have three components, in contrast to Information-driven CTA techniques that typically have only one or the GDTA that has two. The three components are the function name, the decision question capturing the function’s purpose and goal, and the users or user levels that perform or are involved with the function. The particular user levels within the CBRNE response system are discussed in Chapter IV.

![Figure 25: The three components of the CIFA technique's function node, from upper left to lower right; user or user level, function name, and the decision question.](image)

Another difference between the CIFA and the Visual Dataflow languages is how information is consumed. Visual Dataflow languages have multidimensional extensions that allow for two types of consumption for each incoming arc, which will henceforth be referred to as OR consumption (i.e. One at a time and Required) and MR consumption (i.e. Many at a time and Required). OR consumption occurs when one information item is consumed each time the function is executed, as represented in Figure 7 with the “+” function node. In this consumption type, a function can only execute when there is at least one information item queued on the incoming arc. The MR consumption type, in
contrast to OR consumption, allows a collection of information items to be consumed or reviewed on the incoming arc when the function is executed, as represented in Figure 8 with the average function node. MR consumption allows a function to review the queue or history of a particular incoming arc instead of responding instantaneously to each new information item irrespective of its past. This consumption type is very useful, as it has been shown to handle noisy and incorrect information items better than the OR consumption type (Murthy & E. Lee, 2002). As with the OR consumption type, the MR consumption type must have at least one information item on the incoming arc before it can execute. Both of these consumption types are represented in the CIFA technique. Additionally, the CIFA introduces an additional consumption type.

The new information consumption type is designed to represent the optional input item. When analyzing the CBRNE response system using a preliminary CIFA it became apparent that some information items were optional and were simply included to help a function refine its information output, when present. With this new type of information consumption, a functional node can execute without waiting for this information item to be present. This information consumption type can be applied to either single OR or MR consumption types and yields two new information consumption types: OO consumption (i.e. One at a time and Optional) and MO consumption (i.e. Many at a time and Optional).

These four information consumption types are represented visually in CIFA by two different line types and two different arrowhead types, as shown in Figure 26. The OR consumption type, one required information item, is represented by a solid line with a single solid arrowhead (Figure 26a). The MR consumption type, a history or review of
required information items, is represented by a solid line with a double solid arrowhead (Figure 26b). The OO and MO consumption types, the optional information items, can be applied to either of the first two consumption types and are represented by a dashed line (Figure 26c & d).

![Figure 26: The CIFA information four consumption types: a) OR: one item at a time and required, b) MR: multiple items at a time and required, c) OO: one item at a time, optional, and d) MO: multiple items at a time, optional.](image)

The last added feature does not increase the expressiveness of the CIFA but allows the CIFA to be easily divided into logical sections for clarity. The logical sections were based on the sub areas identified in the WDA results. The biggest modeling issue with dividing the CIFA model into sections is denoting information items that are coming from functions represented in other sections. A double border line signifies when an information item in a section is produced by another section (see Figure 27). The “informing” section is denoted in parenthesis underneath the information item name. For example, in Figure 28 “from Victim Care” means the information item “Victim Awareness” is produced in the CIFA section called Victim Care.

![Figure 27: The double border line representing an information item that originates in a different section of the CIFA model.](image)
Cognitive Information Flow Analysis Results

The CBRNE response system was analyzed using two techniques: CWA and GDTA (see Chapter III for results). After the GDTA and CWA were conducted, the results were used to perform the CIFA technique. However, it may be possible to perform the CIFA without first conducting the GDTA or CWA techniques first, but that proof is left as future work.

The CIFA preformed on the CTA results of the CBRNE response system resulted in a model containing approximately 50 functions and over 150 information items. As with the other methods, the CIFA results were broken into four logical sections to facilitate discussions. Those sections are Emergency Evaluation, Incident & Hazard Mitigation, Victim Care, and Command and Information Management. As with GDTA and CWA results in Chapter III, only the results regarding Emergency Evaluation are presented and discussed in this chapter. The remainder of the results is provided in Appendix C.

The CIFA model of the Emergency Evaluation section contains thirteen functions, fifty-two information items, and eight different user levels (Figure 28). The overall goal of Emergency Evaluation is the top most function “Life Safety Assessment” and is defined by the decision question, “What is the assessment with regards to Health and Hazards of this incident?” and produces the “Life Safety Assessment Report.”

The Emergency Evaluation model employs all four consumption types as demonstrated by the “Collection of hazard information” function in the bottom left of
Figure 28. The “Types of symptoms (or lack thereof)” information item employs the MR consumption type. The three vertically placed information items to the left (i.e. “Hazard description information,” “Hazard behavior information,” and “Hazard locations and dispersion”) employ the OR consumption type. The two vertically placed information items (i.e. “Hazardous materials samples” and “Technical Decontamination Status”) below the “Hazard locations and dispersion” information item are connected by OO consumption. The six vertically placed information items on the far left (i.e. “Hazard detection equipment readings,” “Toxic industrial chemical detection readings,” “Background radiation levels,” “Radiation meters,” “Images (photo and video),” and “Air monitoring devices”) employ MO consumption. Thus to produce the “Hazard Reading Report” from the function “Collection of hazard information” the following information items are required: “Types of symptoms (or lack thereof),” “Hazard description information,” “Hazard behavior information,” and “Hazard locations and dispersion” while the remainder of the information items are considered optional. These four required information items encompass the basics of what (i.e. types of symptoms (or lack thereof), hazard description information), where (i.e. hazard locations and dispersion), and what is this hazard going to affect (i.e. hazard description information, hazard behavior information). The other eight information items simply refine and improve the “Hazard Reading Report.” This breakdown of information items based on their consumption types complements the subject matter experts’ feedback regarding the “Collection of hazard information” function in that this function begins producing results at the very beginning of the incident when information is scarce.
Figure 28: The CIFA of the CBRNE response system Emergency Evaluation section.
Comparing GDTA, CWA, and CIFA

The CIFA was developed to combine the GDTA and CWA results based on their different perspectives into a single representation that facilitates system design and in particular system visualization design. The CIFA has five major elements, which will be compared with the GDTA and CWA techniques. These elements are functions, information items, user or user levels, decision questions that capture goals and purposes, and interconnections between the functions. This section compares the analysis methods in detail.

Comparing GDTA and CIFA

The GDTA, if it is a two level analysis, has six components. The six components are overall goal, level 1 sub-goals, level 1 decision questions, level 2 sub-goals, level 2 decision questions, and level 2 information requirements also called situational awareness requirements (Endsley et al., 2003). The overall goal does not translate into the CIFA, which is one disadvantage of the CIFA.

The GDTA’s lowest level sub-goals, those directly associated with information requirements, do not completely or directly translate into CIFA functions for two reasons. The first reason is the different relationships used in the two analysis methods, that is the part-whole relationship in the GDTA and the CIFA’s producer-consumer relationship. The second reason is that the CIFA is also based on the mCWA, which influenced the composition of CIFA functions. The GDTA’s decision questions translate almost directly when the corresponding GDTA function translates into an CIFA function.
The GDTA sub-goal “2.3 On Scene Health and Hazard Assessment” has six sub-goals (see Figure 15). Two of these sub-goals, “2.3.1 Collect Characterizing Information” and “2.3.2 Collect Hazard Information”, translate directly into functions in the CIFA Emergency Evaluation section (Figure 28, bottom left and middle right respectfully). However, the other four sub-goals do not directly transfer. The GDTA sub-goal “2.3.3 Assessment” is broken into two CIFA functions: “Hazard Identification” and “Epidemiological Assessment” (Figure 28, middle left edge and middle left respectfully). This decomposition separates those hazards that have discreet physical locations (e.g. bombs, chemical spills) from those hazards that are airborne or otherwise mobile (e.g. diseases, chemical clouds). The sub-goals “2.3.4 Epidemiological Trace-Forward Investigation” and “2.3.5 Situation Status Report” are combined into the CIFA function “Simulation” (Figure 28, center). However, not all of the sub-goal “2.3.4 Epidemiological Trace-Forward Investigation” was merged into “Simulation,” some of its corresponding information requirements and a portion of its decision question became elements of the CIFA function “Epidemiological Assessment.” The translation, between the GDTA model and the CIFA model, is not simple and, as was the case with the WDA, the CIFA is informed by the GDTA results rather than representing a direct translation of them.

The high-level sub-goals, those without their own list of information requirements, do not translate directly into the CIFA due to the GDTA’s part-whole relationship. Since the CIFA does not use the part-whole relationship and the GDTA’s components (i.e., low-level sub-goals) are, at least partly, translated into the CIFA, the sub-goals representing the whole (i.e., high-level sub-goals) are not translated. The whole goals from the GDTA are only represented in the CIFA if they embody a concept that is
more than the sum of the parts. For example, the sub-goal “2.3 On Scene Health and Hazard Assessment” is a whole goal and is translated into the CIFA model as the function “Life Safety Assessment” (Figure 28 center top) because it is more than the sum of its sub-goals as it represents a fusion of the sub-goals’ results into something meaningful that is to be expressed to higher level goals.

Almost all of the information requirements from the GDTA are represented in the CIFA with many translating directly. However, the information items in the GDTA model are refined when they become information items in the CIFA model. This refinement occurs because some GDTA information items are merged, subsumed, or replaced in the CIFA. The CIFA refines the information items by both clearly representing produced information items and representing an information item as one entity regardless of how many functions use it. The GDTA, in contrast, usually duplicates an information item for each function that uses the information item across the analysis.

Various methods have been used to clarify the GDTA when one information item is used by many functions. One method is to maintain the exact same wording; however, if different functions are created from different documents or from feedback from different subject matter experts, the wording is often similar but not identical, leaving the designer to guess if information items in question are really the same information item or are similar yet different items. Another method of clarifying information items is sometimes employed when there is a collection of information items that are used by several functions. This method utilizes a call out box as was done in the Goodrich et al. (2007) analysis of the wilderness search and rescue response system, as shown in Figure
29. This method works but is only appropriate when the collection of information items can function as a logical unit.

<table>
<thead>
<tr>
<th>Environment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Team Capabilities/Resources</td>
</tr>
<tr>
<td>Weather</td>
</tr>
<tr>
<td>Terrain Features (maps)</td>
</tr>
<tr>
<td>Mountains</td>
</tr>
<tr>
<td>Ridges</td>
</tr>
<tr>
<td>Water/Snow</td>
</tr>
<tr>
<td>Trails</td>
</tr>
<tr>
<td>Flora</td>
</tr>
<tr>
<td>Roads</td>
</tr>
</tbody>
</table>

Figure 29: A call out box for information items used the GDTA model presented in Goodrich et al. (2007). This collection of information items is then collectively referred to as "Environment."

A third method of clarifying related GDTA information items is to assign each information item a unique number. This method adds precision that indicates which information items are actually the same regardless of any variation in the text, but this solution is not as elegant or clear as the method used in the CIFA. This lack of elegance and clarity exists in the GDTA because a designer must physically scan all sub-goals in order to identify all instances in which an information item is used. For example, the information item 0031 is used in all sub-goals of “2.3 On Scene Health and Hazard Assessment,” but that fact is not obvious until one scans through all the sub-goals in Figure 15. The CIFA handles this situation via the visual arrows leading from the information item to all functions using that item. For example, the information item “Pre-assessment report” (bottom left of Figure 28) has three arrows leading from it to the three functions that use this information item, thereby increasing clarity by reducing visual scanning. The arrows provide a clarity and certainty not matched by any of the above descriptive methods for the GDTA.
The relationship between the GDTA and the CIFA is one where most of the GDTA elements translate into the CIFA model; however, the CIFA model contains elements and features that are not present in the GDTA. Many of the information items present in the CIFA are not represented in the GDTA. There are two primary reasons that the GDTA does not represent all of CIFA information items: the GDTA generally does not represent information items produced by a goal and the CIFA draws some information items from the CWA. The GDTA does list some produced information items, such as the item “Results from 2.3.2 collect characterizing information” listed in “2.3.3 Assessment” and this item is translated into the CIFA as “Scene Report” (Figure 28 middle right edge). However, there are other CIFA information items, such as “Life Safety Assessment” (Figure 28 middle top edge) that are the products of the “Life Safety Assessment” function, which has no direct GDTA equivalent. The GDTA does have two information items termed “Reports from field operations” and “Incident Report” listed in “3.1.1 Direct and Control Response Operations” (Appendix A) that are somewhat related to “Life Safety Assessment.” However, unlike the CIFA, the GDTA does not capture where or how these two information items are produced, making their relationship to CIFA’s “Life Safety Assessment” information item unclear. The information item “Life Safety Assessment” was formulated by using information from the original documents and from subject matter experts.

The CIFA representation of users or user levels is also not present in the GDTA. The GDTA technique can be extended, as discussed in Chapter III, to include a “people or groups” section along with information requirements, but this extension is not part of the original description (Endsley et al., 2003). The “people or groups” section is still not
the same as user levels that are in the CIFA as depicted in Figure 29. User levels are an abstraction from the GDTA’s people and groups where a user level represents many different people and groups that share similar responsibilities when viewed from a particular viewpoint, such as their relationship to the robotic system.

Finally, the interconnectivity of the functions in the CIFA is not directly derived from the GDTA because the interconnectivity of the CIFA functions is based on the producer-consumer relationship, whereas the interconnectivity of the GDTA functions is based on a part-whole relationship.

Comparing CWA and CIFA

The CWA is a collection of methods, whereas the CIFA is a single method. All of the CWA methods conducted for the CBRNE response system, as presented in Chapter III, had an effect on the CIFA because they were performed prior to and by the same researcher who performed the CIFA. However, only one CWA method was directly employed and referenced during the construction of the CIFA, the Work Domain Analysis (WDA).

The WDA, as used in analyzing the CBRNE response system, has five vertical axis levels: goal, abstract functions, general functions, processes, and object. The WDA’s abstract functions, general functions, and processes translate into either CIFA information items or functions. The reason these three levels do not translate into both information items and functions nor into one or the other exclusively is due to the fact that the CIFA and the WDA employ different modeling perspectives. The WDA seeks to model the
work domain; whereas, the CIFA seeks to model the flow of information through the functions. Since the techniques do not model the system from the same perspective, the translation from the CWA to the CIFA is not straightforward. The WDA inspires and provides material for the CIFA, but the CIFA is not a functional translation of the WDA. The mapping from the WDA to the CIFA is depicted for a subset of the CBRNE response system in Figure 30. Figure 30 represents the subsystems and functional units of the Emergency Evaluation System captured in the WDA model, as depicted fully in Figure 19. The black square corner boxes in Figure 30 represent elements from the WDA that became information items in the CIFA and the black rounded corner boxes in Figure 30 represent elements that became functions.

The items in the WDA’s objects level become information items in a CIFA, where appropriate. A WDA object can either represent information in a physical sense (e.g. reports, maps, images) or a thing (e.g. ambulance, supplies). If the object represents information, such as maps, then it translates directly into an information item. If the object represents a thing, then it translates into a CIFA as an information item representing the knowledge of the item, but not the item itself. For example, an object such as an ambulance is represented as an information item termed the “availability of an ambulance”.

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Figure 30: The WDA of Emergency Evaluation with indications of the translation to the CIFA. The black square corner boxes represent elements from the WDA that become information items in the CIFA and the black rounded corner boxes represent elements that become functions.
The interconnectivity captured in the WDA model does not translate into the CIFA model in part because the represented relationships are quite different. As discussed in Chapter II, the WDA uses part-whole and means-end relationships whereas the CIFA uses a producer-consumer relationship.

The relationship between the WDA and the CIFA is one where the WDA elements mostly translate to, or are subsumed by, the CIFA; however, the CIFA contains elements and features not present in the WDA. These additional elements are the result of incorporating the results of both the WDA and the GDTA. Most of the decision questions present in the CIFA are not represented in the WDA, but are instead represented in the GDTA.

Many of the information items present in the CIFA are not represented in the WDA. There are two primary reasons the WDA does not represent all of the CIFA information items: the WDA does not represent information items directly and the CIFA draws many information items from the GDTA results. The WDA represents information items indirectly through objects, meaning that the WDA lists an object such as “hazard detection equipment” (Figure 19), whereas the CIFA lists the information produced by the object such as “hazard detection equipment readings” (Figure 28). However, the WDA in listing information items indirectly does not capture all information item types that can be represented in the CIFA, especially the transformation of information items by non-objects such as humans. For example, the CIFA has an information item called “Scene Report,” which is produced by the function “Collection of characterizing information” (see Figure 28 middle right side). The WDA model also has an element called “Collection of characterizing information;” however, the WDA has no
representation for what is produced by this element (Figure 30: in the Function Units by General Function cell on the right side).

The CIFA representation of users or user levels is also not present in the WDA. The CWA, to its credit, does include methods that focus on users or user levels: relevant social groups, communication flow map, and identify demand on work competencies also known as activity analyses (see Chapter II). These methods had a direct influence on the user levels for CIFA in large part because these methods were performed first.

Finally, the interconnectivity of the CIFA’s functions has similarities and differences to the mCWA’s ConTA. The CbTA employs a two-step action-knowledge structure that generally represents paths that flow from a knowledge state to an action node and then repeats. Similarly, the CIFA represents paths that flow from an information item to a function node and then repeats. However, CbTA and CIFA differ in the meaning represented by the paths and in the type of data represented by their respective knowledge or information nodes. The CbTA’s paths link the current knowledge state to the action to be performed to the next resulting state of knowledge. For example, if the current state is the knowledge node, “need to defuse bomb,” then the path may link to the action to be performed “defuse bomb” to the resulting knowledge state of “bomb defused.” The CbTA paths have a very different meaning from the CIFA paths. The CIFA paths link functions to both the information items used in the function’s execution and information items produced as the result of a function’s execution. For example if the function node is “defuse bomb” then the input information item may be “the type of bomb” and the resulting information item may be “bomb defuse status.” The CIFA allows its data nodes to represent any type of information, whereas the CbTA only
allows its data nodes to represent states of knowledge. A state of knowledge can easily be composed of many information items, meaning that the CIFA inherently provides more information details.

The difference in the type of information represented and the meaning of the paths led to the CBRNE CbTA results not being used explicitly in the creation of the CBRNE CIFA. There are some correlations between the two methods; however, these correlations are artifacts of representing the same domain and not because the CbTA informed the CIFA. The parallelism and partial ordering that were the important factors in employing statecharts over decision ladder in performing the CbTA are captured in the CIFA (see Chapter III). Functions in the CIFA can execute as soon as they have all of their required information items without regard to other functions. This allows multiple functions to execute concurrently, representing parallelism. The CIFA represents partial ordering through the production of information items: functions that rely on other functions being performed first are blocked from executing until the required functions produce the needed information items. Therefore, the parallelism and partial ordering represented by statecharts for CbTA are represented in the CIFA.

CIFA Advantages

The use of the CIFA in analyzing the CBRNE response system has highlighted a number of advantages of this technique including focus or perspective, clarity, identification of information bottlenecks, highlighting of teamwork, and ease of translation into prototyping. The focus advantage is primarily based on the flow of
information; however, unlike the CbTA, which is similarly being based on the flow of knowledge states, the CIFA provides greater expressiveness because it models all types of information and can express different means of consuming the information. The focus on information highlights the SA requirements for each and every function, which has been proven important for human-robotic interaction (Drury et al., 2003; Scholtz et al., 2005; Yanco & Drury, 2004).

The GDTA also focuses on SA requirements; however, the GDTA’s presentation is not as crisp as that provided by the CIFA, nor does the GDTA’s presentation express how functions transform information as clearly as the CIFA’s presentation. For example, the CIFA clearly represents that the “Hazardous Reading Report” is produced from the “Collection of hazard information” function by consuming or using four to twelve information items. It can be argued that when the GDTA includes the extensions from Flach et al. (2004) (i.e., information requirement represented in an abstraction decomposition), the GDTA has as much expressive power as the CIFA. However, these extensions do not achieve this expressive power through a single model diagram but a collection, whereas the CIFA is a single unified model diagram.

Another advantage of the CIFA is the ability to pinpoint information bottlenecks both in terms of particular functions and in terms of particular users. An information bottleneck is defined as a point X in the system where a greater than average number of subsequent functions cannot be executed without the information from this point X being provided. An information bottleneck is defined mathematically here as the number of functions that require a particular information item over the average number of functions that require any particular information item. The identification of information bottlenecks
becomes critically important in interaction design, as these identified information items are the most important to the users and therefore may need be treated differently in the design. The information item “Pre-assessment report” in Figure 28 (center and towards the bottom) is an information bottleneck as three important functions require it and those functions’ outputs are subsequently required for many other functions. The identification of this information item as a bottleneck correlates with subject matter experts reports that the “Pre-assessment report” is one of the very first pieces of information that is developed and many early response decisions are based on that report. When designing new systems these information bottlenecks can be critical spots where human-robotic systems may improve or worsen the information flow and thereby greatly affecting the overall CBRNE response system.

The CIFA’s focus on the information flow through functions facilitates HRI design. The identification of the required input and output information (i.e. information flow) is crucially important for any given function to be performed or directed through the interface between humans and robots. Prior research has demonstrated that input information (i.e. situation awareness) is important to HRI (Drury et al., 2003; Scholtz et al., 2005; Yanco & Drury, 2004). Output information subsequently becomes input information for other functions; therefore, by extension, output information is important to HRI. The CIFA technique can express all of the input and output information succinctly and clearly, thereby supporting HRI design.

The advantage of the CIFA in highlighting teamwork is a direct consequence of its incorporation of identifying users or user levels for each function. If a function has more than one user associated with it, then there is a strong potential that these users are
either part of a team or may benefit from being part of a team. This advantage is especially useful in new domains because it can identify how new functions could be performed through teamwork.

Summary

The Cognitive Information Flow Analysis (CIFA) technique has been developed to analyze the information flow throughout a system. The CIFA, in this case, has been developed based on the results of the GDTA and CWA. The GDTA and CWA models do not directly translate into the CIFA model, but both heavily inform the resulting CIFA model. The GDTA and CWA inform, rather than directly translate into the CIFA because the CIFA views the system from a different perspective. Just as a CWA cannot directly translate into a GDTA, both the GDTA and CWA do not directly translate into the CIFA. The CIFA may be performed without first conducting a GDTA or a CWA; however, the proof of such CIFA will be left as future work. The CIFA was designed to analyze revolutionary and semi-revolutionary systems; yet, it should also be applicable to evolutionary systems, though proof of this capability is also left for future work.

The CIFA has a number of abilities and advantages. The ability to express the interconnectivity of the various system subcomponents with an elegant focus on the flow of information items is its most fundamental characteristic. The CIFA also expresses partial orderings of these subcomponents via their relationship within the flow of information. The focus on the information flow provides the ability to identify information bottlenecks. The addition of users or user levels provides the ability to
highlight teamwork, both current and potential. Finally, the CIFA serves as a guide to developing the command and control of semi-revolutionary systems, which will be discussed further in subsequent chapters.
CHAPTER VI

VISUALIZING THE SYSTEM

These proposed robotic technologies for the CBRNE response system will use computer-based visualization for both command and control of the robots, and to provide feedback from the robots. The goals of the visualization are to present the information in a manner that supports decision making at different user levels, supports communication between different user levels, and allows the hierarchy of decision-makers to recall past information. Supporting these decision-makers requires that three problem areas be addressed: information abstraction and presentation, relaying information to the different user levels, and temporal navigation. This research proposes the General Visualization Abstraction (GVA) algorithm to address the information abstraction and presentation problem area. The relaying of information to different user levels is addressed by the introduction of the Decision Information Abstracted to a Relevant Encapsulation (DIARE) object concept. The last problem area, temporal navigation, is partially addressed by using the results of the GVA algorithm and DIARE to index time, thereby assisting temporal navigation. This chapter presents the GVA algorithm, the DIARE object, and temporal navigation concepts.
General Visualization Abstraction (GVA) algorithm

Abstraction is critical to decision making as its absence means that the decision-maker must manually parse the important information from the unimportant information and manually group related information. Both of these tasks, parsing and grouping, are cognitively demanding (Wickens et al., 2003). Furthermore in multi-scale visualizations, abstraction is important as some information details cannot be represented at a particular scale due to limitations in screen size without abstraction. Information abstraction involves three operations that are performed on the information items; selection, grouping, and representation. The relevancy feature of effective incident management visualizations is usually addressed through selection (Cai et al., 2006).

An information item in the CBRNE response system has two components: its location or location range in the visualization, and its meaning \((m)\). The location has five dimensions (5D): latitude \((x)\), longitude \((y)\), elevation \((e)\), time \((t)\), and information scale \((s)\). An information item can, therefore, be represented mathematically as a sextuplet \([x, y, e, t, s, m]\) where each of the values in the sextuplet can be either a single value (e.g. elevation of 10 meters) or a range of values (e.g. from 13:15 to 15:47). A solution that uses all available information components and is appropriate for novel information and unanticipated decision-making will advance the visualization field and provide a foundation on which subsequent work in information abstraction can be built.

The proposed solution is an algorithm called the General Visualization Abstraction (GVA) algorithm. The GVA algorithm essentially computes a value for each information item that is then used to determine its selection, grouping, and representation.
The value represents how important displaying a particular information item is to the decision-maker given a certain context. The GVA algorithm computes the value by focusing on two classes of information: historically and currently relevant information, and novel and emerging information. The GVA algorithm then presents the salient information (i.e. information in the two classes) in higher detail and the less important information (i.e. information outside the two classes) in lower detail or not at all. This idea is similar in concept to the Focus plus Context visualization technique (Baudisch et al., 2002) described in Chapter II. The Focus plus Context technique applies the idea to the display screen; whereas, the GVA algorithm applies the idea to the three parts of abstraction: selection, grouping, and representation.

The Visual Score

Mathematically, the GVA algorithm produces a visual score (v) for each information item. The value of the visual score determines if the information item will be selected (i.e. displayed), if the item should be grouped with other items, and how it will be displayed (e.g. high resolution, low resolution). Information items are candidates for grouping if their visual scores are too low to be displayed in great detail, but high enough to be displayed at least as residue. Residue provides evidence that should lead the user to believe that more details or a particular information piece may be found by performing a clearly indicated action in the visualization (Jul & Furnas, 1998). If these information item candidates for grouping are close geographically and logically, then they will be grouped. If instead these information item candidates are not close in either respect, they
will be displayed as their visual score dictates. Algorithm 1 expresses the general approach the GVA algorithm uses to select, group, and display information items as outlined above.

**Algorithm 1: The GVA algorithm method to select, group, and display information items.**

For each time step:

For each information item, $i$

Compute: the item’s visual score, $v_i$

For each information item, $i$, that is displayed (i.e. $v_i \geq v_{residue}$)

If any of its displayed neighbors are logically similar

Then group the item, $i$, with these neighbors

Else

If $v_i \geq v_{details}$

Then display the item, $i$, in full details.

Else If $v_i \geq v_{low}$

Then display the item, $i$, in low details.

Else If $v_i \geq v_{residue}$

Then display the item, $i$, as residue.

Else

The item, $i$, is not displayed

Where:

$v_{details}$ is the minimum visual score required for an item to be displayed in full details.

$v_{low}$ is the minimum visual score required for an item to be displayed in low details.

$v_{residue}$ is the minimum visual score required for an item to be displayed as residue.

The GVA algorithm calculates each information item’s visual score ($v$) by evaluating if the item belongs to either information class, (i.e., historically and currently relevant information, or novel and emerging information.) These two major information classes are each comprised of two sub-classes. The first major information class is a composition of historically relevant information and currently relevant information. The second major information class is a composition of novel information and emerging information. However, the GVA algorithm will be limiting if it does not use more factors
then simply the item’s association with either major information class. Two other factors are required for robustness: predetermined importance and an item’s contribution to the overall visual clutter.

The *predetermined importance* factor is added to express knowledge known a priori by the system designer regarding the inherent importance of certain information items above or below the average or generic information item (e.g. active bombs are very important). Therefore, predetermined importance is an offset that can raise or lower the visual score but will have no effect if predetermined importance is unavailable for the information item.

The concept of visual clutter provides a balance between displaying all possibly useful information and displaying so much information that the screen becomes visually cluttered. *Visual clutter* is the condition when the density of information displayed on the screen is greater than some optimal level, resulting in a breaking of the constant information density principle (Woodruff et al., 1998). *Constant information density* is the principle that if the amount of information displayed is greater than some threshold, then displaying more information degrades the performance and effectiveness of the system. When information is too dense it is considered cluttered. The GVA algorithm’s clutter factor directly addresses this concern.

The visual score ($v$) of an information item is expressed in Equation 1 as a composition of the two aforementioned factors, predetermined importance and clutter, and the item’s association with the two information classes. Each component of the equation is denoted with square brackets (i.e. [ ])) and constants are added to scale the
components’ relative contributions to the visual score. These two major information classes are combined using a max function, which preserves the relationship that the visual score is derived from either class, whichever is greater.

**Equation 1: The six components of the GVA algorithm’s visual score calculation.**

\[ v = k_1 [\text{Predetermined Importance}] - k_2 [\text{Clutter}] + \max\left\{ \begin{array}{l}
k_3 [\text{Historically Relevant}] + k_4 [\text{Currently Relevant}] \\
\text{or } k_5 [\text{Novel}] + k_6 [\text{Emerging}] \end{array} \right\} \]

Where:

- \( k_n, n = 1, 2, \ldots \) are scalar constants used to determine the relative importance of each factor.
- \( [\phantom{\text{}}] \) represents a component that returns a value in the range from -1 to 1.

Two other common approaches to the selection problem, domain specific heuristics (Jul & Furnas, 1998; Cai et al., 2006; Ward, 2002) and random sampling (Ellis & Dix, 2006a), discussed in Chapter II can be expressed in terms of Equation 1. The domain specific heuristic approach can be represented in Equation 1 by setting constants \( k_3 \) to \( k_6 \) to zero, thereby using only the first two components (i.e., the predetermined importance and clutter factors.)

The random sampling approach can also be represented by Equation 1 by setting all constants except \( k_2 \) to zero, as random sampling is based solely on the clutter factor. The domain specific heuristic approach can also degrade into the random sampling approach if the information item has no predetermined importance value, which occurs when the information item is unanticipated by the visualization designer. It is possible that after some time the operator will assign an importance value to the unanticipated information item; however, this approach relies on the operator making wise choices and is static with regard to time.
The random sampling approach (Ellis & Dix, 2006a) uses only the clutter factor, to select randomly some information items based on the notion of the constant information density concept (Woodruff et al., 1998). The random sampling approach is limiting because it is incapable of assigning value to information items that are more important, by any metric, than other items. Therefore, the random sampling approach is only appropriate when all information items always have the same value. This situation is improbable when the visualization is representing a dynamic real-time, real-world system (e.g. CBRNE). The GVA algorithm, therefore, is designed to answer the selection problem in an intelligent manner, even when there are unanticipated non-uniformly valued information items, by utilizing all six components in Equation 1, in particular the last four factors.

The six components of Equation 1 will be further expanded upon to illustrate how, algorithmically, the components can be measured and computed to yield the visual score. The six components are predetermined importance, clutter, historically relevant, currently relevant, novel, and emerging. Before developing the details as to how to compute each factor, the element $m_i$, or meaning in the information item’s sextuplet, [$x, y, e, t, s, m$], needs to be revisited. The meaning of an information item can be considered to have two elements: a collection of information types or classes to which it belongs and a particular value. For example, the information item, an undetonated bomb, can be in the class “bomb” with the value being “undetonated”. This separation of meaning into two components is used in the computation of several of the factors.
The Predetermined Importance Component

The predetermined importance component in Equation 1 can be computed as a simple lookup table based on the meaning of the information item (see Algorithm 2). If the information item does not have a lookup table value then the importance is zero and this factor has no effect on the information item’s visual score.

Algorithm 2: The calculation of Predetermine Importance.

If information item’s, $i$, meaning, $m_i$, is in the lookup table

$[Predetermined\ Importance_i] = \text{LookupTableValue}(m_i)$

Where the function LookupTableValue($m_i$) returns a value from -1 to +1 depending on the predetermined importance of $m_i$.

Else

$[Predetermined\ Importance_i] = 0$

The Clutter Component

Equation 1’s clutter component is constructed from two components: percentage obstructed (\% obstructed) and similarity to other visible information items (similarity to visible). The \% obstructed factor lowers the visual score for information items that consume a large amount of screen space for their current representation (e.g. full details consume more space than residue). This factor verifies that if the GVA algorithm determined that an item should use a large amount of screen space, then the item will have the visual score to support that decision. The \% obstructed factor can be computed as the result of an algorithm that answers the question: “How much available viewing space is used by this information item?”

The second factor, similarity to visible, is designed to lower visual scores of information items in large, similar groups that are currently being displayed. This does
not mean that the information items are not displayed; instead, the group of items may be
displayed with less detail so that more items can be displayed without causing the screen
to be overly cluttered. The similarity to visible factor can be computed as the result of an
algorithm that answers the question: “Are there other information items with similar
meanings to this information item?”

Using these two subcomponents, % obstructed and similarity to visible, the clutter
component in Equation 1 can be expressed algorithmically by Algorithm 3.
Algorithm 3: The calculation of Clutter.

For information item, $i$,

$$S_i = ScreenSpace(x_i, y_i, e_i, s_i)$$

Where the function $ScreenSpace(x_i, y_i, e_i, s_i)$ returns the number of screen units used by $i$, a positive, possible zero value and $S_{total} \geq S_i$.

$$S_{total} = ScreenSpace(x_v, y_v, e_v, s_v)$$

Where the function $ScreenSpace(x_v, y_v, e_v, s_v)$ returns the total number of screen units available, a positive nonzero value and $S_{total} \geq S_{empty}$.

$$S_{empty} = EmptyScreenSpace(x_v, y_v, e_v, s_v)$$

Where the function $EmptyScreenSpace(x_v, y_v, e_v, s_v)$ returns the number of unused screen units, a positive possible zero value.

$$[% \text{Obstructed}_i] = 1 - \frac{S_{empty} - S_i}{S_{total}}$$

Let $C_i$ be the set of information items, $c$, that are members in the information item, $i$, class(es).

$$U_i = \sum_c C_i\text{Visible}(c, t)$$

Where the function $Visible(c, t)$ returns a value from 0 to 1 depending on how much detail is displayed at time $t$ (e.g. full detail returns 1, not visible returns 0).

$$N_i = |C_i|$$

meaning the number of items in $C_i$.

$$[\text{Similarity to Visible}_i] = \begin{cases} \frac{U_i}{N_i} & \text{if } N_i > 0 \\ 0 & \text{if } N_i = 0 \end{cases}$$

$$[\text{Clutter}_i] = k_T[\% \text{Obstructed}_i] + k_B[\text{Similarity to Visible}_i] =$$

$$k_T \left(1 - \frac{S_{empty} - S_i}{S_{total}}\right) + k_B \begin{cases} \frac{U_i}{N_i} & \text{if } N_i > 0 \\ 0 & \text{if } N_i = 0 \end{cases}$$

Where $k_T, n = 7, 8$ are scalar constants used to determine the relative importance of each component.

The Historically Relevant Component

The historically relevant component of Equation 1 is a continuity factor that extends an information item’s importance from the recent past into the present. The historically relevant component’s purpose is to prevent information items from toggling quickly between being very relevant one moment and not being relevant the next
moment, which may cause the item to disappear from the screen. Instead, a continuity factor is used to gradually reduce the relevancy of the information items with time, thereby gradually fading from the viewing screen, which forces the visual representation to shift from a higher detail level, to a low level detail, to not being displayed at all (see Algorithm 4).

The concept of information items disappearing slowly while providing clear evidence that they are slowly disappearing is called information fading. This concept is important to include in the GVA algorithm, as it is known that removing items from a visualization quickly without the user’s knowledge leads to poor system understanding (Wickens et al., 2003).

**Algorithm 4: The calculation of Historically Relevant.**

For information item, \( i \),

\[
HR_i = \sum_{t=t_{now}}^{t_{past}} \text{Visible}(v_i, t)
\]

Where

The function \( \text{Visible}(v_i, t) \) returns a value from 0 to 1 depending on how much detailed is displayed at time \( t \) (e.g. full detail returns 1, not visible returns 0).

\( t_{past} \) is some time in the past.

\( t_{now} \) is the current time.

\( T_i = t_{now} - t_{past} \), \( T_i \) is a positive nonzero number because \( t_{now} > t_{past} \).

\[
[Historically\ Relevant_i] = \frac{HR_i}{T_i}
\]

The Currently Relevant Component

Equation 1’s *currently relevant* component is composed of two subcomponents: relevancy and expiration. The *relevance* subcomponent ensures that the information item is relevant, while the *expiration* subcomponent ensures that the information item is
current. Relevancy is a positive term indicating how useful this information item is to the current situation. Expiration is a negative term that ensures an information item will disappear slowly, if that item has been removed from the system.

The relevancy factor is based on a measurement of interaction to determine relevancy. The relevancy factor can be computed, therefore, as the result of an algorithm that answers the question: “Has this information item been interacted with lately and, if so, how?”

There are two other approaches, in addition to the expiration approach, of dealing with information items that have been removed from the system, both of which can lead to poor system understanding. The first approach causes the item to instantly disappear from the visualization when removed from the system. Causing an item to disappear instantly when removed from the system is in violation of the slow information removal concept and can lead to poor system understanding. The second approach does nothing to indicate that an item has been removed, that is, it ignores the item, which results in the item continuing to be displayed. Ignoring the removal event and not indicating it in the system may lead the user to believe that the information is current when it is not, an undesirable situation. Therefore, expiration is the best approach in dealing with information removal as it indicates to the user that the information has expired while still adhering to the slow information removal concept. The expiration factor can be computed as a result of an algorithm that answers the question: “How long ago has this information item been removed if indeed it has been removed?”
Using these two subcomponents, relevancy and expiration, the clutter component can be expressed algorithmically by Algorithm 5.

**Algorithm 5: The calculation of Currently Relevant.**

For information item, $i$,

Let $A_i$ be the set of interaction pairs, $\{t_a, I_a\}$, for $i$ such that $t_{now} \geq t_a \geq t_{now} - t_{too long ago}$.

Where:
- $t_a$ is the time of the interaction.
- $I_a$ is the type of interaction.
- $t_{now}$ is the current time.
- $t_{too long ago}$ is a constant time in the past that is considered too long ago from $t_{now}$ to matter.

$R_i = \sum A_i \text{ValueOfInteraction}(I_a) \ast \text{SomeDecayFunction}(t_{now} - t_a)$

Where:
- ValueOfInteraction($I_a$) is a function that returns a value from 0 to 1 denoting the importance of this type of interaction (e.g. editing item returns 1, mouse hover returns 0.5, etc).
- SomeDecayFunction($t_{now} - t_a$) is a function that returns a value from 1 (when $t_{now} - t_a \leq 0$) to 0 (when $t_{now} - t_a \geq t_{too long ago}$).

Let $A_{all}$ be the set of interaction pairs, $\{t_a, I_a\}$, for all information items such that $t_{now} \geq t_a \geq t_{now} - t_{too long ago}$.

Compute $R_{all} = \sum A_{all} \text{ValueOfInteraction}(I_a) \ast \text{SomeDecayFunction}(t_{now} - t_a)$.

Then $[\text{Relavency}_i] = \begin{cases} \frac{R_i}{R_{all}} & \text{if } R_{all} > 0 \\ 0 & \text{if } R_{all} = 0 \end{cases}$.

If $i$ has a removal time, $t_{removal}$

$E_i = \text{SomeDecayFunction}(t - t_{removal})$.

Else

$E_i = 0$

Then $[\text{Expiration}_i] = E_i$.

Therefore,

$[\text{Currently Relevant}_i] = k_9[\text{Relavency}_i] + k_{10}[\text{Expiration}_i] = k_9 \begin{cases} \frac{R_i}{R_{all}} & \text{if } R_{all} > 0 \\ 0 & \text{if } R_{all} = 0 \end{cases} + k_{10}E_i$

Where $k_9, n = 9, 10$ are scalar constants used to determine the relative importance of each component.
The Novel Component

The Equation 1 novel component is essentially a calculation of an item’s uniqueness, where uniqueness represents how different the information item is from all other information items. The uniqueness factor can be computed as the result of an algorithm that answers the question: “How different is the meaning of this information item from all other information items?” as provided in Algorithm 6.

Algorithm 6: The calculation of Novel.

For information item, \( i \),

Let \( C_i \) be the set of information items, \( c \), that are members in the information item, \( i \), class(es).

\[ U_i = |C_i|, \text{ meaning the number of items in } C_i, \text{ a positive, possible zero number.} \]

\[ N_i = \text{total # of information items, a positive nonzero number.} \]

\[ [\text{Novel}_i] = \frac{N_i - U_i}{N_i}. \]

The Emerging Component

Equation 1’s emerging component is composed of two subcomponents: youth and relevancy. The first subcomponent, youth, represents how long ago an information item was created or entered into the system. The more recently an information item has been created, the younger, and therefore more emergent, the item is. The youth factor can be computed as the result of an algorithm that answers the question: “How recently has this information item been created?”

The second subcomponent, relevancy, has the same meaning as it does in the currently relevant component, that is, how useful is an information item for the current situation; however, it is implemented differently. The relevancy feature is a component of the emerging term because not all emerging information items are visually important and
displaying an emerging, but unimportant information item may not be useful and may distract from other useful information items. For example, the system displays all bombs in an effort to determine which bombs to defuse first and then both a cow (i.e. something unimportant) and a bomb-defusing robot enters the system. Both the cow and the robot are unique to this system; however, the robot is clearly more relevant than the cow and therefore should be rewarded for its relevancy and displayed more saliently than the cow.

The relevancy subcomponent for the novel component in Equation 1 cannot be computed in the same manner as it was computed in the currently relevant component because a new information item has no interaction history. Therefore, the relevancy factor subcomponent for the novel component will be based on whether or not items with similar meaning are visible. For example, if the user is currently interacting with bomb information items then the bomb information items will be very visible when a new bomb item is created and this new bomb item will also be deemed relevant. The relevancy subcomponent is computed as the similarity to visible subcomponent of the clutter component (see Algorithm 3’s second component). Thus by using similarity to visible as the emerging component’s means of computing relevancy, the novel and emerging components in the max function from Equation 1 counteract the clutter’s use of similarity to visible in its computation. Therefore, information items that are novel and emerging do not have their visual scores reduced, as there are other items with similar meanings currently being displayed. If similarity to visible was not a factor in the novel and emerging component, information items that are too similar to other items currently being displayed will likely appear as residue or be grouped with similar items, thereby potentially hiding the fact that they are new to the system.
Using the two subcomponents youth and relevancy, the emerging component can be expressed algorithmically, as provided in Algorithm 7.

**Algorithm 7: The calculation of Emerging.**

*For* information item, *i*,

- **Compute** \( Y_i = \text{SomeDecayFunction}(t_{\text{now}} - t_{\text{created}}) \)
  
  **Where:**
  - \( \text{SomeDecayFunction}(t_{\text{now}} - t_{\text{created}}) \) returns a value from 1 (when \( t_{\text{now}} - t_{\text{created}} \leq 0 \)) to 0 (when \( t_{\text{now}} - t_{\text{created}} \geq t_{\text{too long ago}} \)).
  - \( t_{\text{now}} \) is the current time.
  - \( t_{\text{created}} \) is when the information item was created.
  - \( t_{\text{too long ago}} \) is a constant time in the past that is considered too long ago to matter.

\[
[Youth_i] = Y_i
\]

Let \( C_i \) be the set of information items, *c*, that are members in the information item, *i*, class(es).

\[
U_i = \sum C_i \text{Visible}(v_c, t)
\]

**Where** the function \( \text{Visible}(v_c, t) \) returns a value from 0 to 1 depending on how much detail is displayed at time *t* (e.g. full detail returns 1, not visible returns 0).

\( N_i = |C_i| \), meaning the number of items in \( C_i \).

\[
[\text{Relevancy of Emerging}_i] = [\text{Similarity to Visible}_i] = \begin{cases} 
\frac{U_i}{N_i} & \text{if } N_i > 0 \\
0 & \text{if } N_i = 0
\end{cases}
\]

\[
[\text{Emerging}_i] = k_{11}[\text{Youth}_i] + k_{12}[\text{Relevancy of Emerging}_i] = k_{11}Y_i + k_{12} \begin{cases} 
\frac{U_i}{N_i} & \text{if } N_i > 0 \\
0 & \text{if } N_i = 0
\end{cases}
\]

**Where** \( k_{1n}, n = 1,2 \) are scalar constants used to determine the relative importance of each component.

**Information Item Representation**

The last GVA algorithm component represents the information with a shape. The shape is partly determined by the high/low resolution distinction. The high-resolution information may be presented in a manner that preserves as much distribution information as possible. **Distribution information** arises from grouping individual
information items together into a single new super information item. The locations of individual information items in the super item become the distribution information of the super item. The distribution information can be encoded using a color component such as saturation, luminosity, or transparency. Color components have been successfully used to represent several levels of a particular value in other contexts (Wickens et al., 2003). The low-resolution information can be represented with an icon, symbol, or marker shape thereby preventing the low-resolution information from detracting from the high-resolution information.

The Halo Concept

One may ask the question, “What happens if an information item has a high visual score and should be displayed, but the item is not geographically within the currently viewable area of the interface?” This case is handled by adding a halo area surrounding the main window view in order to display these information items (see Figure 31) and by adding a new component to Equation 1. The display screen is thereby split into two components: a main view area and a halo area. The halo area has been employed in earlier human robot interaction work (Humphrey, Henk, Sewell, Williams, & Adams, 2007). The halo concept is structurally similar to the Focus plus Context visualizations (Baudisch et al., 2002) in that it is designed to provide context to the main viewing area, which is the focus. The information items in the halo area, unlike the Focus plus Context, do not have their full geographic location expressed. Information items in the halo area are placed according to their relative location from the main view without any indication
of distance from the main view, except that they reside beyond that area. The halo area allows the user to maintain awareness of information items outside the main view and provides an indication of how to navigate the visualization to view the items in more detail without using a distorted visual geometry, as is applied with the Focus plus Context visualization. Information items in the main view area still have their full geographic location information displayed, whereas information items in the halo area only have a portion of their geographic location information displayed, (i.e., their relative location to the main view.)

Figure 31: The halo area is the space surrounding the map in the center. In this figure, the halo area has four information items displayed as four round icons (three on the bottom and one on the right.)
Equation 1 is modified for use with the halo concept by adding an in-view component (see Equation 2). The in-view component only affects items displayed in the halo area and does not affect information items in the main view. This component reduces the visual score of information items as they move farther away from the main view. Without a reduction in visual score based on distance from the main view, all information items not displayed in the main view will be displayed in the halo area, rendering the halo area ineffective. The in-view component, therefore, prevents unnecessary information items from cluttering the halo area while still allowing important information items to be displayed regardless of their distance from the main viewable area. The in-view component can be computed, as depicted in Algorithm 8, as the result of an algorithm that answers the question: “Is the information item in the viewing space and if not, how close is it?”

**Equation 2: The calculation of the GVA algorithm’s visual score for use with the Halo concept.**

\[
v = k_0[In View] + k_1[Predetermined Importance] - k_2[Clutter] + \max\{k_3[Historically Relevant] + k_4[Currently Relevant] \text{ or } k_5[Novel] + k_6[Emerging]\}
\]

Where:
- \(k_n, n = 0,1, ...\) are scalar constants used to determine the relative importance of each component.
- \([ \ ]\) represents a component which returns a value in the range from -1 to 1.
Algorithm 8: The calculation of In-View.

For information item, \( i \),

If information item’s, \( i \), volume, \((x_i, y_i, e_i, s_i)\), is completely contained inside the viewing space,

\((x_v, y_v, e_v, s_v)\),

Compute \( D_i = 0 \)

Else

Compute \( D_i = \text{SomeDecayFunction}\left( \text{Distance}\left( (x_i, y_i, e_i, s_i), (x_v, y_v, e_v, s_v) \right) \right) \)

Where:

\( \text{SomeDecayFunction}(\quad) \) is a function that returns a value from 1 (when \( D_i = 0 \)) to 0 (when \( D_i \geq D_{too\ far} \)) and \( D_{too\ far} \) is a distance when an information item is too far away to consider context for the main view.

\( \text{Distance}\left( (x_i, y_i, e_i, s_i), (x_v, y_v, e_v, s_v) \right) \) is a function that returns a the geometric distance between the center of these two volumes, a positive nonzero number.

\([\text{In View}_i] = D_i\)

GVA Algorithm Summary

In summary, the General Visualization Abstraction algorithm developed in this dissertation goes beyond simple rule-based heuristics and random sampling techniques. It facilitates abstraction by employing a more robust understanding of information item importance to compute a visual score. The visualization abstraction provided by the algorithm filters, groups, and displays information items to support decision-making, even when the information types and the decision types are unknown.

Decision Information Abstracted to a Relevant Encapsulation (DIARE)

The purpose of sharing information across user levels is either to provide support for the user’s decision or to provide evidence in support or opposition of another user’s decision. Only the information relevant to this purpose needs to be shared: nothing more
(e.g. all system information) and nothing less (e.g. shared flags). Many visualization sharing techniques are either inflexible (e.g. shared space and large-scale displays), indirect (e.g. shared flags and shared annotations), or require translation (e.g. instant messaging, shared flags, and shared annotations). See Chapter II for a discussion of each of these sharing techniques. None of these methods shares collections of information items directly or explicitly allows users at different user levels to view the information differently from each other. The Decision Information Abstracted to a Relevant Encapsulation, or DIARE, concept is designed to address these shortcomings.

DIARE is based on the idea that evidence for a particular decision can be represented as a defined volume in the visualization’s information space spanning the six components $[x, y, e, t, s, m]$. This defined volume becomes an object or DIARE object and contains information relating to that particular decision (i.e. range of $m$) in terms of a spatial area (i.e. range of $x$, $y$, and $e$), time range ($t$), and detail range ($v$). A DIARE object will act as a super information object that can be shared between user levels and can itself become an element in the visualization. For example, several DIARE objects can be created by the person supervising the robots during an area survey and later someone else can search an overlapping area for any DIARE objects that deal with unusual items, which can cause the visualization to display one or two DIARE objects as information items on the map.
Comparing DIARE with Activity Sessions

The DIARE concept is similar to the activity sessions concept (Tomaszewski & MacEachren, 2006), discussed in Chapter II, but differs in two key ways. An activity session is designed to conceptually represent the same thing as a DIARE object: a logical collection of information entities that illustrate an idea or problem; however, the mechanics are very different. Activity sessions employ shared annotations with time to capture the idea, albeit indirectly, whereas a DIARE object encapsulates the information to be shared and shares the information directly and completely. The DIARE object does not require the translation that an activity session requires (i.e., mapping from an artifact back to the related information items.)

Sharing Across User Levels

The DIARE object allows other users to view the shared information items in any way that the general visualization supports because a DIARE object represents a collection of information items in a volume of space rather than a static image of the information items. This approach implies that different user levels can view a DIARE object in different manners in order to best support their needs.

For example, if the operator user level believes that the information being viewed currently indicates that there may be a hidden secondary hazard device, the operator can capture that collection of information and form a DIARE object. The DIARE object can then be easily shared with the supervisor user level for notification or guidance. The supervisor can view the information items in the DIARE object in the same manner as the
operator or in a different manner (e.g. different detail level) to perhaps support another task the supervisor is directing. Later this DIARE object can be recalled and subsequently incorporated into another DIARE object; for example, relating the hidden secondary hazard device DIARE object to the task of defusing the device.

Visualizing the DIARE Object

Visually a DIARE object may be displayed as an interactive movie clip accompanied with additional notes regarding the object’s purpose, see Figure 32. Figure 32 has four components that comprise a representation of a DIARE object: DIARE context, DIARE notes, visualization window, and DIARE time. The DIARE context (the top portion of Figure 32) depicts this DIARE object on a timeline with other DIARE objects to provide a temporal context. The DIARE notes section (the right section of Figure 32) allows users to add notes regarding this DIARE object and ask and answer questions related to the DIARE object. When a user opens a DIARE object, the visualization window that is displayed to the user when the user is not dealing with a DIARE object is reduced in size and displayed in the bottom left (see of Figure 32). The DIARE timeline (on the very bottom of the visualization window in Figure 32) allows the user to move through the time encapsulated in the DIARE object.
DIARE Summary

The DIARE object is a novel concept in two ways. First, a DIARE object represents a collection of information items in a volume of space rather than a static image of the information items. Secondly, users may view the DIARE object in as many ways as the general visualization supports. Both of these attributes are not present or are severely lacking in other information sharing techniques.

Temporal Navigation

The last problem area is temporal navigation in the CBRNE response system. Navigation through time is often aided with time marks or the highlighting of key frames or time segments (Wickens et al., 2003). A classic example of time marks is the scenes in
the scene selection menu on DVDs. Research regarding navigation through time exists (Dachselt & Weiland, 2006) and this author is not proposing a new means of navigating through time, but rather a new manner of creating time marks automatically for information visualization, such as the incident system. The idea is to create time marks automatically based on the outputs of the previous two solutions: the GVA algorithm and the DIARE objects. The time marks may be added when the GVA algorithm highlights novel or emerging information items or when DIARE objects are created. The automatic creation of time marks will facilitate a more effective navigation through time.

Summary

The proposed robotic technologies for the CBRNE response system will use computer-based visualizations that must address three problem areas: information abstraction and presentation, relaying information to different user levels, and temporal navigation. This chapter proposed the General Visualization Abstraction (GVA) algorithm to facilitate the information abstraction and presentation, the Decision Information Abstracted to a Relevant Encapsulation (DIARE) object concept to provide information sharing, and using the GVA algorithm and DIARE object results together to assist temporal navigation. Together, these concepts will improve abstraction and presentation, relaying information to different user levels, and temporal navigation in direct-able visualization system such as the proposed CBRNE robotic system.
CHAPTER VII

PROPOSED DESIGNS OF EXPERIMENTS

“We put forward the idea that empirical evaluation of visualisations on its
own is methodologically unsound due to the generative nature of
visualisation techniques. However, if empirical evaluation is used in
conjunction with reasoned justification then this may lead to a reliable and
strong validation of the visualisation.” - (Ellis & Dix, 2006b)

The purpose of the following design of experiments is to empirically evaluate the
two visualizations proposed by this thesis, the General Visualization Abstraction (GVA)
algorithm and the Decision Information Abstracted to a Relevant Encapsulation (DIARE)
concept. The empirical evaluation aims to validate the visualizations’ justifications. This
chapter presents the GVA algorithm design of experiments first, followed by the design
of experiment for the DIARE concept.

Design of Experiments for the GVA algorithm

The GVA algorithm’s purpose is to address the information abstraction and
presentation problem in direct-able multi-scale visualizations (see Chapter VI for more
details). The GVA algorithm determines the abstraction and presentation of information
items in the visualization based on a visual score, which is determined by its importance
in two classes of information: historically and currently relevant information, and novel
and emerging information. These classes along with a few other components (e.g. clutter)
form Equation 2 (repeated below), which has a total of seven components. The GVA
algorithm will be evaluated through two different experiments where each experiment is
designed to test different hypotheses that were used in constructing the GVA algorithm.

**Equation 2: The calculation of the GVA algorithm’s visual score (from Chapter VI)**

\[ v = k_0[\text{In View}] + k_1[\text{Predetermined Importance}] - k_2[\text{Clutter}] + \max\{k_3[\text{Historically Relevant}] + k_4[\text{Currently Relevant}] \]
\[ \text{or } k_5[\text{Novel}] + k_6[\text{Emerging}] \]

Where:

- \( k_{\nu}, n = 0, 1, \ldots \) are scalar constants used to determine the relative importance of each component.
- [ ] represents a component which returns a value in the range from -1 to 1.

**Hypotheses**

The hypothesis behind the GVA algorithm is that an item *can* be valued, and in turn visualized, based on its relationship with the two information classes: historically and currently relevant information, represented by terms 3 and 4 in equation 2; and novel and emerging information, represented by terms 5 and 6. Both experiments will seek to inform the validity of this hypothesis in different ways. The first experiment will evaluate whether or not these two information classes do indeed improve the visualization of information items. Therefore, the first experiment will compare two conditions: (1) neither class is used (i.e., \( k_0 \neq 0, k_1 \neq 0, k_2 \neq 0, k_3 = k_4 = k_5 = k_6 = 0 \)) and (2) both information classes are used (i.e., \( k_0 \neq 0, k_1 \neq 0, k_2 \neq 0, k_3 \neq 0, k_4 \neq 0, k_5 \neq 0, k_6 \neq 0 \)). The first condition is akin to the standard approach often used to visualize information items, whereas the second condition uses the GVA algorithm. The **hypothesis of the first experiment is that the GVA algorithm (i.e., condition 2) will be quantitatively preferred, have lower workload, improve situational awareness, and allow the operator to perform discovery type tasks faster than the condition not using the GVA (i.e., condition 1).** If condition 2 is
better than condition 1, the experiment will have shown that the GVA algorithm is an improvement.

The second experiment is designed to provide more insight into the fundamentals of the GVA algorithm and is a follow up to the first experiment. The purpose of the second experiment is to evaluate the importance of the two information classes that comprise the GVA individually. This experiment will compare three conditions: (1) both classes are used (i.e., \( k_0 \neq 0, k_1 \neq 0, k_2 \neq 0, k_3 \neq 0, k_4 \neq 0, k_5 \neq 0, \) and \( k_6 \neq 0 \)); (2) only the historically and currently relevant information is used (i.e., \( k_0 \neq 0, k_1 \neq 0, k_2 \neq 0, k_3 \neq 0, k_4 \neq 0, k_5 = 0, \) and \( k_6 = 0 \)); and (3) only the novel and emerging information is used (i.e., \( k_0 \neq 0, k_1 \neq 0, k_2 = 0, k_3 = 0, k_4 = 0, k_5 \neq 0, \) and \( k_6 \neq 0 \)). The hypothesis for the second experiment is that the full GVA algorithm (i.e., condition 1) will be quantitatively preferred, have lower workload, improve situational awareness, and allow the operator to perform discovery type tasks faster than either of the partial GVA algorithm conditions (i.e., conditions 2 and 3). If condition 1 is better than both conditions 2 and 3, the experiment will have shown that both information classes are important and integral components of the GVA algorithm.

Design of Experiments

The GVA algorithm will be evaluated in two separate, yet sequential, experiments: the first experiment will have two conditions and the second will have three conditions. Each condition will be tested with two different trials. The design employed for both experiments will be a within-subject replicated Latin square design (Maxwell &
Delaney, 2003). The replicated Latin square design will assist in controlling ordering effects, which may occur with both within-subject factors (i.e., independent variables): condition and trial. Therefore, the first experiment will have four levels and the second experiment will have six levels.

Participants

The design of experiments is a repeated-measures design where the first experiment will have four levels and the second experiment will have six levels. The minimum sample sizes for four levels and for six levels in a Latin square design needed to detect an effect of 0.75 with a power of 0.80, an $\alpha$ equal to 0.05, and a minimum correlation of 0.4 are 28 and 36 participants respectively (Maxwell & Delaney, 2003). Therefore, the total number of participants required complete these experiments will be 64: 28 participants for the first experiment and 36 participants for the second experiment. All participants will be adults at least 18 years or older. Participants will be screened for four requirements: at least a high school education, computer competency, no experience with the maps used in this experiment, and no prior exposure to the interface itself. Participants will complete a background questionnaire to determine prior robot and computer gaming experience. All participants will have normal or corrected-to-normal vision.
Tasks

The two tasks for both GVA experiments will be based on a realistic CBRNE scenario and will be of two different types. One task type will require the participants to assume the Team Leader role and manage the robots by assigning and monitoring their tasks. The second task type will require the participant to assume the Operations Chief role and monitor the situation along with adding and managing response related information. These two tasks are designed to provide feedback on how the GVA algorithm’s abstraction and presentation of information items will perform for a variety of user types.

Data collection and Metrics

The evaluation’s dependent variables include a number of objective and subjective measures. The subjective measures include the 10-Dimensional Situational Awareness Rating Technique (10D SART) (Taylor, 1989; Endsley, 1995b; Endsley & Garland, 2000), NASA-Task Load Index (NASA-TLX) (Hart & Staveland, 1988), the Multiple Resources Questionnaire (MRQ) (Boles, Bursk, Phillips, & Perdelwitz, 2007), post task questionnaires, and a final questionnaire. 10D SART was chosen over other SA measurement methods because these evaluations are similar to field evaluations and techniques such as Situation Awareness Global Assessment Technique (SAGAT) may alter participants’ workload (Endsley, Selcon, Hardiman, & Croft, 1998; Taylor, 1989). The 10D SART will provide an indication of the GVA algorithm’s impact on situational awareness. The NASA-TLX and the MRQ will likewise provide an indication of impact
on perceived workload. The post task questionnaires will be designed to support the findings in SA, workload, and performance. The final questionnaire will be designed to ascertain the participants’ thoughts regarding the GVA algorithm performance.

The objective dependent variables include time to complete each subtask in each task, the time to find particular items during each task (i.e., a discovery type task), and the reaction time to particular items during each task (i.e., a discovery type task). The time to complete each subtask in each task will provide a sense of the overall performance impact of the GVA algorithm. The time to find particular items and the reaction time to particular items will provide a sense of how effective the GVA algorithm is at abstracting and presenting information items in two different cases: new items and already existing items. The task will also directly probe the participant’s SA through various subtasks. One subtask will require participants to notify other responders that a new bomb has been identified. This requires SA levels 1 and 2 and the metric will be how long it takes the responders to perform this subtask from when the new bomb information is added to the visualization. The second subtask will require the participant to answer whether responders may enter a very hazardous area. This subtask requires level 3 SA and will be measured based on both the accuracy of the response and how long it takes the participant to respond.

Design of Experiments for the DIARE concept

The DIARE concept’s purpose is to facilitate information sharing between users or across time. The DIARE concept accomplishes its facilitation by providing the means
to capture a moment in time as a DIARE object, to share this object, and to search for other DIARE objects. The DIARE concept, unlike the GVA algorithm, does not have independent subcomponents nor any straightforward baseline, meaning that either the DIARE object is present in its entirety, thereby providing sharing, or it is not present and the interface provides no inherent sharing. Therefore, the DIARE concept does not lend itself to condition-based evaluations as the GVA algorithm does. The DIARE concept, therefore, will only be evaluated subjectively.

Hypothesis and Design of Experiment

The DIARE concept hypothesis is that it is subjectively found useful and easy to understand by the participants. The DIARE concept will not be evaluated using conditions, as with the GVA algorithm. Instead, the DIARE concept will be evaluated using questionnaires designed to be both qualitative and quantitative in order to ascertain how the participants interacted with the DIARE concept and the utility it provided. The DIARE concept will be evaluated alongside the GVA algorithm during each of the GVA algorithm’s experiments. The DIARE concept will be evaluated in its own task, which will be performed after all GVA algorithm tasks have been performed. The DIARE concept task will be the same for both GVA experiments.
Participants

The number of participants for the DIARE concept evaluation will be 64, as the evaluation occurs in conjunction with the GVA algorithm evaluations. The participants, being the same as those evaluating the GVA algorithm, will be screened for the same requirements (see above).

Tasks

The DIARE task will require the participants to both interact with existing DIARE objects and to create new DIARE objects. The interaction will involve exploring, searching for, and viewing existing DIARE objects.

Data collection and Metrics

The DIARE concept evaluation’s dependent variable will be a subjective questionnaire following the task. The questionnaire will be designed to ascertain, qualitatively and quantitatively, the participants’ perceptions of utility and performance of the DIARE concept. Emphasis will be placed on exploratory questions regarding the DIARE concept’s interaction, strengths, weaknesses, and relevancy. The DIARE concept evaluation will provide a few objective measures in order to provide additional insight into the functionality and interaction with the DIARE concept. These objective measures are time to create a DIARE object, time to access an already created DIARE object, and time to find a particular DIARE object.
CHAPTER VIII

PRELIMINARY RESULTS FROM PILOT EVALUATIONS

The purpose of the pilot study was to explore the potential usefulness of the GVA algorithm. The pilot study employed a simplified version of the GVA algorithm as this version did not perform grouping and the performance was not optimized. Furthermore, the full interface was not used, instead only the map subcomponent was employed.

Hypothesis and Design of Experiment

The pilot study tested two conditions, namely, whether or not the GVA algorithm was operational. The pilot study conditions are similar those proposed the first GVA algorithm evaluation. The pilot study hypothesis is that the condition using the GVA algorithm will be performed faster, the participants will locate more ambulance information items, and the participants will prefer using the GVA algorithm.

Participants

The pilot study had six participants. They were orally screened to meet the same requirements as specified for the outlined evaluations.
Tasks

The pilot evaluation task was a simple task. The participants located ambulance items (i.e., icons) and dragged them to a pre-specified location (i.e., the 50-yard line in the stadium). The participants were shown the ambulance icon before they performed the task. The system added one hundred items to the visualization at a frequency of one every quarter of a second. The locations and types of the items displayed were random, but repeated exactly the same for every task (i.e., every task used the same random number sequence). There were fifteen total ambulance icons added to the visualization. The participants were instructed that as soon as the icons began to appear they were to begin dragging the ambulance icons to the 50-yard line as quickly as they could. The participants were told when all items had been added, but were not told the number of ambulance icons. The participants were told to click the “all done” button when they thought they had moved all the ambulance icons. The task took slightly longer than one minute to perform. The participants were first trained for 30 seconds using the interface with and without the GVA algorithm operating. The participants performed the task twice, once with the GVA algorithm operating and once without it operating. The ordering was reversed between each participant. The task when using the GVA algorithm is represented in Figure 33. Enlarged items in Figure 33 are due to recent interaction or have recently been added. The task when not using the GVA algorithm is represented in Figure 34. All icons are the same size.
Figure 33: A screen shot from the pilot experiment using a basic version of the GVA algorithm.

Figure 34: A screen shot from the pilot experiment not using the GVA algorithm.
Data collection and Metrics

The pilot study recorded the task duration and the number of ambulance icons the participants moved. After both tasks, the participants answered a simple questionnaire regarding their preferences. The questionnaire is replicated in Figure 35.

**Figure 35: The pilot study questionnaire.**
Results

The pilot study hypothesis is that the condition using the GVA algorithm will be performed faster, the participants will find more ambulance icons, and the participants will prefer using the GVA algorithm. The evaluation analysis included a statistical analysis of both the task duration and the number of ambulance icons located and moved. All statistical tests are paired two-tailed student t-tests with Type I errors set to 0.05 and Cohen’s d (ES(d)) and Hedges’ g (ES(g)) where used to compute effect size measured. The average time GVA was 54.0 seconds (SD = 11.0) and the average time for the non-GVA was 51.1 seconds (SD = 7.3). This difference was not significant (p = 0.260, t(11) = 1.187) and contradicts what was expected according to the hypothesis. The average number of ambulance icons found for the GVA was 15 (SD = 0) and the number found for the non-GVA was 13 (SD = 1). The difference in the number found between the two conditions was significant (p < 0.01, t(11) = 4.49) and the effective size is very large (ES(g) = 11.78, ES(d) = 3.55). The difference in the number of ambulance icons found confirms the hypothesis that the GVA better supports a searching task. The difference also may explain why there was not any significance between the task durations. It is logical to assume that if the participants were required to find all 15 ambulances, then the non-GVA trials would have been possibly much longer in duration and therefore would have yielded a significant difference in times.

The pilot study questionnaire results are presented in Figure 36 and Figure 37. The data captured from questions that listed “first version” and “second version” were translated to GVA and non-GVA. This translation was accomplished by first replacing the labels and then by reversing the numbers of the scale. For example in questions 3, 4,
and 5, if the participant’s second version was the non-GVA version and he or she answered a “2” then it was converted to a “6” so that higher numbers were always for the GVA (see Figure 37). On average, the GVA was found to be easier to use than the non-GVA, though not by a lot (Figure 36). There was one participant (e.g. 2) who thought the GVA was harder than the non-GVA. Upon further questioning, the participant indicated that having the GVA change items sizes was confusing; however, this participant was the only one who found this to be the case. The cognitive difficulty was found on average to be lower for the GVA, reflecting GVA’s support in assisting the participant in discovering ambulance icons (Figure 37). The participants reported that their awareness of the situation was greater for the GVA (Figure 37), indicating that the GVA provided a visualization that possibly improved their confidence that they were finding all the ambulances. This indication is supported by the fact that the participants did indeed find more ambulances with the GVA. Lastly, the GVA was preferred, supporting the hypothesis.
Figure 36: The difficulty reported for the pilot study as captured in questions 1 and 2 of the questionnaire (Figure 35).
In summary, the pilot study supported two of the three components of the hypothesis. The GVA algorithm allowed the participants to find more ambulance icons and was preferred over not using the algorithm. However, the last hypothesis component was not supported as the GVA algorithm did not allow the participants on average to perform the task faster than without using the GVA algorithm.
CHAPTER IX

PROPOSED SCHEDULE

Institutional Review Board (IRB) submission for user testing approval by October 31

Propose on November 14th

Finish implementing the DIARE concept by December 1st

Finish implementing the GVA algorithm by December 16th

Start advertising for the first experiment on January 2nd

Start the first experiment on January 8th

Compute first experiment results by February 2nd

Start advertising for the second experiment on February 2nd

Start the second experiment on February 9th

Compute second experiment results by March 1st

Finish writing Journal article on results by March 31st

Finish writing Thesis on May 15th

Defend in late May/early June
Summary of Contributions

In summary, the contributions of this work are as follows. The first contribution is the cognitive task analyses (i.e., the GDTA and CWA techniques) of the human-centric CBRNE response system for the use of incorporating robotic technology. The second contribution is the addition of the extensions to the GDTA and CWA techniques to accommodate a human based system as well as the CBRNE response system scope. The third contribution is the introduction of the CIFA technique to provide a bridge between the GDTA and CWA results and a system implementation. The fourth contribution is the formation of the human-robotic interaction levels for a CBRNE response system, which includes the addition of one new user level beyond those of Goodrich and Schultz (2007). The fifth contribution is the formulation of methods that transform the CIFA results into human-robot interaction visualizations. The sixth contribution is the GVA algorithm framework and the corresponding algorithm implementation and validation. The seventh contribution is the DIARE object concept, implementation, and validation. The final contribution is the implementation and user system evaluation (i.e., robots and visualizations) for use in CBRNE incidents.
APPENDIX

GDTA, CWA, and DA results (possibly the results from BYU analysis as well)

Appendix A: The Complete Results of the GDTA.

Appendix B: The Complete Results of the CWA.

Will be present in the final version.
Appendix C: The Complete Results of the CIFA.

Will be present in the final version.

Appendix D: The Greater Nashville Exercise with Robots.

Will be present in the final version.
REFERENCE


