Attention Allocation for Human Multi-Robot Control:
Cognitive Analysis based on Behavior Data and Hidden States

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***Abstract*— Human multi-robot interaction exploits both the human operator's high-level decision-making skills and the robotic agents' vigorous computing and motion abilities. While controlling multi-robot teams, an operator's attention must constantly shift between individual robots to maintain sufficient situation awareness. To conserve an operator's attentional resources, a robot with *self-reflect* capability on its abnormal status can help an operator focus her attention on emergent tasks rather than unneeded routine checks. With the proposing self-reflect aids, the human-robot interaction becomes a queuing framework, where the robots act as the clients to request for interaction and an operator acts as the server to respond these job requests. This paper examined two types of queuing schemes, the *self-paced Open-queue* identifying all robots' normal/abnormal conditions, whereas the *forced-paced shortest-job-first (SJF) queue* showing a single robot's request at one time by following the SJF approach. As a robot may miscarry its experienced failures in various situations, the effects of imperfect automation were also investigated in this paper. The results suggest that the SJF attentional scheduling approach can provide stable performance in both primary (locate potential targets) and secondary (resolve robots' failures) tasks, regardless of the system's reliability levels. However, the conventional results (e.g., number of targets marked) only present little information about users' underlying cognitive strategies and may fail to reflect the user's true intent. As understanding users' intentions is critical to providing appropriate cognitive aids to enhance task performance, a Hidden Markov Model (HMM) is used to examine operators' underlying cognitive intent and identify the unobservable cognitive states. The HMM results demonstrate fundamental differences among the queuing mechanisms and reliability conditions. The findings suggest that HMM can be helpful in investigating the use of human cognitive resources under multitasking environments.**

Keywords- Human-robot Interaction; Cognitive Assistant; Task Switching; Hidden Markov model; System Reliability; Scheduling.

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1. INTRODUCTION

Robotic agents have been widely used to support humans in completing a variety of dangerous tasks, such as searching for trapped victims in risky environments or replacing human soldiers on a battlefield. In most of the human multi-robot interaction, robots operate with relative independence and are capable of operating in parallel, whereas an operator is usually incapable to control multiple robots at a time and regularly shifts her attention from one robot to another to monitor the robots' status and acquire situation awareness (SA). The robots' effectiveness therefore greatly depends on ***periodic*** human intervention. For example, a mobile robot could successfully explore the environment and perform the assigned tasks for a period of time only requiring an operator's attention when it detects targets (e.g., trapped victims). In other words, the overall system performance is significantly affected by the effectiveness of operators' attention allocation (Chen, 2009; Lewis, 2013; Prewett et al., 2010; Verma and Rai, 2013).

Human-robot interaction (HRI) examines the uses of robotic systems and evaluates the interaction in human-robot teams. Goodrich and Schultz (2007) suggested the quality of communication between human operators and robotic agents is essential to achieve an appropriate interaction as well as an efficient HRI structure. Therefore, to better design the communication schemes in human-robot teams, it is critical to understand how the operators allocate their attentional resources to communicate multi-robot teams. As an operator's attentional resources are typically shared among a variety of tasks, however, even periodic human interventions may not be able to sufficiently serve the robots' emergent requests. Previous research (Cummings and Mitchell, 2008) demonstrated that humans are incapable of shifting attention between robots to obtain the required SA in an effective and efficient manner. As a result, operators need assistance to maintain sufficient SA in complex and time-critical situations. Follow-up studies (Chen et al., 2010; Crandall et al., 2011; Cummings et al., 2012) used a timeline display to assist operators in identifying bottlenecks and potential scheduling conflicts. The results suggested that HRI performance can be improved by appropriately scheduling an operator's attention to only those robots that are in need of interaction.

To enhance task performance, automated robot self-reflection is frequently used to improve the HRI processes under a variety of complex conditions (Chien et al., 2012b; Wang et al., 2011). Automatically reporting a robot's abnormal status not only eliminates an operator's need to monitor, but also allows an operator to focus on critical interactions, thereby increasing the number of robots serviced during this interval. Although automated supports could conserve human cognitive resources, applying automated applications to direct an operator's attention from an ongoing task to a specific task may decrease the operator's SA and potentially increases the cognitive loads to acquire the necessary information while responding to a robot request (Eriksen and Yenh, 1985; Kiesel et al., 2010).

Inappropriately directing an operator to service a particular robot has been found to have a negative effect on overall performance in human-robot systems (Crandall et al., 2011). Most of time, operators may be less inclined to use relevant automated aids if the gain is offset by the mental cost of switching attention (Bainbridget, 1983; Crandall et al., 2011; Endsley and Kaber, 1999). Koch et al. (2010) concluded that switching costs arise from "*both transient and long-term carry-over of task-set activation and inhibition*" and may lead to the perception of a higher workload and lower overall system effectiveness. These costs are associated with impaired performance in task-switch paradigms, as compared with repetition trials (Kiesel et al., 2010). Therefore, operators may take more time to complete mixed-task blocks (i.e., alternating between two or more tasks) than in repetitive single-task situations (Koch et al., 2005). Although enhancing robot autonomy can provide assistance with the control process and allow operators to interact with each robot as needed, the aforementioned studies suggested that the required interactions may greatly increase an operator's perceived cognitive loads. Therefore, identifying an effective interaction scheme to satisfy operators' cognitive demands as well as to respond to robots' requests in time is indeed the most critical aspect of enhancing the HRI performance.

Understanding the association between the operators' cognitive states and their resulting behaviors is needed for improving human supervisory control in highly automated systems (Crandall et al., 2005; Olsen and Wood, 2004). In HRI fields, researchers employ two primary methods to investigate the supervisory processes. The first approach examines the overall system performance, such as the number of targets detected (Chen, 2009; Chien et al., 2012b), area explored (Scerri et al., 2011), or vehicles' damage levels (Chien et al., 2016; Imbert et al., 2014; Miller and Parasuraman, 2007). The other approach characterizes operators' attention allocation, such as the response rate in answering the robots' requests (Crandall and Cummings, 2007; Mekdeci and Cummings, 2009; Mercado et al., 2016). However, when an operator makes choices among alternatives, similar actions may be a result of different intentions. For example, a robot can be terminated because the assigned task has been successfully completed or the robot is incompetent to perform the task. Therefore, these conventional measures (overall performance and response rate) might be unable to reflect the underlying cognitive factors that significantly influence operators' intent and behaviors.

Conventional approaches evaluate the HRI performance by the overall task results that merely reflect the observable behaviors and fail to examine operators' cognitive intentions or decision-making processes. In order to capture more insights from human supervisory control processes, we adopt the Hidden Markov Model (HMM) to explore the human's cognitive states (Baum et al., 2011). HMM is a well-established method for parameter estimation and has been shown useful in modeling human behaviors and discovering unobservable human intentions in a wide range of application domains, such as astronaut supervisory monitoring behaviors (Hayashi et al., 2005) and collaborative web search processes (Yue et al., 2014). HMM analysis provides advantages over conventional approaches by making the explicit contexts for human supervisory control and assisting with interpretation of unobservable human intentions.

As decision makers' attention allocation may greatly influence by their scheduling strategies, the potential gains in various system developments of effective means to convey task recommendations warrant further investigation. Two different types of cognitive queues are evaluated in this paper, namely the *Open-queue and SJF-queue methods*. The *Open-queue* method presents all the robots' conditions and sends out failure alarms at the same time. The *SJF-queue* method, a more sophisticated queuing mechanism, presents only one robot request generated by the shortest-job-first principle. The *Open-queue* scheduling mechanism was previously seen in Cummings et al. (2007) study, in which a timeline display was used to show each intelligent agent's current status and to project the upcoming tasks. As the SJF approach is known to maximize throughput (Garey et al., 1976), we therefore develop a single event queuing display along with the SJF discipline. Prior research suggested that the operators with poor attentional control strategies tended to rely more heavily on automated aids, regardless of the system reliability levels (Chen et al., 2011; Chen and Terrence, 2009). To address these issues, *two different system reliability levels* are also investigated in this study, in which the robot failures are misdiagnosed (i.e., not detected) to simulate the effect of unreliable system. Both the conventional analysis and the HMM approach are used to measure the differences between the queuing types and reliability levels. We hypothesize that *H1: High reliability level will result in better overall performance, covering both primary and secondary tasks*. Since the SJF method is known to maximize throughput (Garey et al., 1976), we hypothesize that *H2: The SJF-queue method will outperform* *the Open-queue approach across all the experimental scenarios*. Moreover, a reliable queuing system can optimize attentional resources in both queuing conditions, whereas an unreliable queuing system may provide insufficient information and fail to effectively direct operators' attention. Hence, we hypothesize, H3*: In both the Open-queue and SJF-queue schemes, the high reliability will lead to better outcomes than the low reliability condition*. As decision makers must prioritize tasks/alarms in the Open-queue, we hypothesize that H4*: Operators will experience heavier workloads in the self-paced Open-queue condition*, *which could be a result of a higher level of perceived frustration,* since no clear guidance will be provided in the Open-queue scheme. In other words, fewer workloads would be reported in the SJF-queue condition, regardless of the reliability levels. Additionally, since operators are allowed to perform the tasks based on their own strategies in the Open-queue scheme, we therefore hypothesize H5*: HMM's transition patterns will be more complex under the Open-queue group*.

2. RELATED WORK

2.1. Human-Robot Interaction (HRI)

Human-agent teaming for multi-robot control is a complex process that requires both skilled operators and delicate system designs to effectively enhance overall HRI performance. To maintain appropriate situation awareness (SA), an operator must efficiently manage her cognitive resources and allocate attention among a variety of tasks. The situation in which one operator controls a team of robots is considered to be a more exhaustive and complex task than managing a single robot, which requires the operator to simultaneously manage attentional resources among robots to maintain necessary SA. Various factors affecting human-robot supervisory control processes (such as perceived cognitive load, allocation of attention, and cognitive capacity) have been studied in previous research (Donmez et al., 2010; Lewis et al., 2010; Nagavalli et al., 2015; Visser and Parasuraman, 2011). Attentional control has been identified as one of the most critical factors influencing human supervision of robot teams, since most of the HRI tasks inevitably involve multitasking conditions (Chen and Barnes, 2014, Chappelle et al., 2011). However, due to limited cognitive resources, human operators may encounter enormous difficulties in responding to robots' requests for interaction in a timely fashion.

The degree of attention allocation in multi-robot control tasks varies from completely manual control to supervisory control with a high level of automation (LOA). Sheridan and Verpank (1978) developed the first LOA taxonomy, which classifies autonomy into ten levels based on the range of control that an operator could manage. Operators must (partially) manually control the machines and make decisions in low LOA conditions, while fully autonomous systems are used under high LOA conditions. In other words, the intelligence of robots determines the human supervisory control behaviors, which may allow an operator to use cognitive resources to focus on higher level mission-related goals (e.g., decision selection) without spending resources on low level tasks (e.g., monitoring processes). However, while applying automation, operators and automated agents may perform similar operations with different purposes. These contradictory intentions may result in unexpected outcomes leading to serious system failures. Thus, while directing operators' attention to necessary (automated) events, it is important to maintain appropriate system awareness and resolve the potential conflicts between a human's intentions and system suggestions in a variety of diverse situations.

Several solutions have been proposed to assist operators in managing sufficient cognitive resources in order to maintain adequate awareness and appropriate performance for multi-robot control tasks. Cummings et al. (2007) designed the schedule management aids that included timeline displays to show upcoming events, decision support tools to provide potential solutions, and task summary panels to recap mission statuses, along with color schemes to visualize a variety of tasks. Although the provided aids are beneficial in presenting the potential schedule bottlenecks and warning the operator of possible conflicts, the authors concluded that showing the potential problems without providing appropriate solutions is not more helpful than the baseline design (i.e., no visualizations). In addition, the vivid visualization aids of emerging problems may distract operator attention and interrupt the primary tasks.

The interruption management approach is therefore proposed to lessen operators' switching costs and allow the operators to have higher levels of SA during the tasks. Ratwani et al. (2007) used a tracking history list to remind the operators of the original tasks before the interruption. Chen et al. (2010) provided a changing history list to record what occurred during the interruption to recover the overall SA. However, providing support through a visual summary or a history of prior events may consume large amounts of cognitive resources to process the represented information, in which the (endless) list could lead operators to fix their attention on the changes to that list and neglect the important awareness of the ongoing tasks. Therefore, with respect to effectively managing cognitive resources, providing cognitive support to assist operators in achieving efficient attentional control is critical to enhancing HRI performance.

2.2. Cognitive Issues in HRI

Human interaction with multi-robot teams has been widely explored and raised many research questions. Prior research investigated the effects of robot team size on performance (i.e., metrics of tasks) and the influences of the robot's LOA (i.e., metrics of robots). The *metrics of tasks* examine the number of robots that an operator can effectively control in various contexts (Lewis et al., 2010); whereas the *metrics of robots* identify the amount of effort that an operator has to invest in operating a single robot.

These metrics provide thorough mechanisms to evaluate the quality of human multi-robot interaction and to measure the difficulties in a number of task contexts.

However, the appropriate performance thresholds for a robot may vary widely depending on the task requirements. For example, a robot that paints street lines requires a higher degree of precision than a street-sweeping robot that collects rubbish from streets. As a consequence, robots typically need to be serviced on demand rather than sequentially, which introduces an additional complexity to human supervisory control of multi-robot teams. In addition, previous studies indicated that decision makers often over-estimated their cognitive capabilities and failed to identify optimal scheduling strategies in controlling robot teams (Crandall et al., 2011; Sheridan and Tulga, 1978). The performance degradation therefore may not be simply caused by the size of robotic teams or the difficulty of assigned tasks but can be greatly affected by switching attention between tasks. To determine human strategies in multitasking environments, Cummings and Mitchell (2008) developed a neglect tolerance model that examined operators' interactions with robots in a sequence of control episodes. The identified timeline intervals in their work were applied to a fan-out equation to predict the threshold for a human operator to control multi-robot teams.

The attention allocation of multiple concurrent tasks such as in controlling multi-robot can be referred to as the cost of switching attention (Goodrich et al., 2005; Kiesel et al., 2010). To appropriately manage limited cognitive resources, task realization largely depends on a human's capabilities of attention allocation (Crandall and Cummings, 2007; Wickens and Hollands, 1999). In the research of Steinhauser and Hübner (2008), the cost of task switching is compared with repetition tasks and controlled processing tasks. Kiesel et al. (2010) further investigated the global switching costs of both repetition tasks and switching tasks as well as the local switching costs of simple repetition tasks. Switching tasks produce greater costs (i.e. more failed tasks and longer reaction time) and even lead to higher frequency of error rates (Steinhauser and Hübner, 2008). Therefore, providing aids to direct human's attention to various conditions is important to help operators allocate attention to emergent tasks as well as to maintain efficient awareness of the original task (Altmann and Trafton, 2007; Goodrich et al., 2005).

2.3. Cognitive assistance in HRI

In time critical missions, it is particularly important that an operator can allocate attention effectively since the failure of managing a high-priority task in a timely manner not only lessens the effectiveness of the system, but also potentially results in disastrous consequences (Crandall et al., 2011). To mitigate the effect of operators' cognitive limitations, applying cognitive assistance to manage attention resources is required, in which several directions were developed to improve operator attention allocation in HRI-related tasks.

First, a thread of approaches focuses on visualizations that present the status, plans, and progress of robots in the system. This kind of visualization approach implicitly directs the operators to specific tasks and when to perform them. Cummings and Mitchell (2008) investigated timeline visualizations for unmanned aerial-vehicle (UAV) systems by presenting a schedule of anticipated events. Through the display, the operator can identify and select the task to perform and decide when to perform it. A subsequent study by Cummings et al. (2007) found that a single operator can control multiple UAVs with decision support tools, but the influences of the provided decision making tool on operator performance and SA cannot always be predicted.

The second research thread proposes a warning system that detects potential critical events and sends an alert or signal explicitly to the operator. Lee et al. (2004) explored how the alert strategy and modality affected automobile collision-warning systems that mitigated distractions and directed a driver's attention to the car ahead when it unexpectedly braked. They found that graded alerts led to a greater safety margin, resulting in fewer inappropriate responses to nuisance warnings and higher trust ratings to the system aids. Meanwhile, they suggested that the vibrating seat designed in their study as a haptic alert was perceived as less annoying and more appropriate, which suggested the graded haptic alerts offered a great opportunity to apply context awareness in a safety-critical domain. Donmez et al. (2009) investigated whether sonification (continuous auditory alerts) can inform the operator about the state of a monitored task and thereby support UAV control. Their results showed sonification can support operators in predicting states of monitored tasks but might also interfere with other ongoing tasks (i.e., too much distraction).

Another direction works to explicitly provide suggestions or dictums for the operator to pay attention at a specific event at a given time. Crandall et al. (2011) modeled the operator's attention in order to lead the human's attention to the most effective event as well as the most needed event to perform the tasks. Their results showed that operators' attention allocation was effectively devoted to the primary goal (target detection) but was not as effective in the secondary mission, maintaining the robotic agents' safety (Crandall et al., 2011). In other words, the operators were unable to effectively allocate their attention to the secondary missions in complex and time-critical situations. The rate of system presentation of elements in a (timeline) display varied from a few seconds to several minutes; however, human detection rates remained constant. Since concentrating attentional resources on different events is problematic, Eriksen and Yenh (1985) suggested that providing a cuing signal directed the concentration of attentional capacity into needed events. According to the previous studies from different directions of attention allocation, allowing robots to self-report abnormal states seems to be a fundamental approach of reducing the switching costs and enabling the operator to better prepare for the robots' abnormalities. However, before applying the self-report aids, it is important to understand the effects of different types of cognitive mechanisms (such as the Open-/SJF-queue methods in this study) and investigate the potential influences resulting from various types of cognitive assistance.

2.4. Assessing cognitive assistance

Examining the effectiveness of different attention allocation methods requires the development of proper performance assessments. Existing literature generally measures the task performance (Chien et al., 2012b), experienced workload (Lewis et al., 2010), or scheduling intervals (e.g., neglect tolerance model in Cummings and Mitchell (2008). For example, NASA Task Load Index (NASA-TLX; Hart and Staveland, 1988) is a subjective multidimensional assessment instrument, in which participants report experienced workload with a task, an intelligent agent, a robotic system, etc. Additionally, the neglect tolerance model shows such operator interactions with an individual robot and the sequence of control episodes based on different time intervals. However, these approaches only identify the differences by analyzing the overall results (e.g., number of targets found, workload score, or interaction time), which is incapable of (1) identifying the fine-grained difference of interactions during the whole task completion course; and (2) revealing the human's decision-making strategy and latent cognitive intentions. As understanding operators' cognitive intentions and attentional strategies in multitasking environments is important, to further investigate these issues, a dedicated approach is needed to better understand complex human interactions.

To permit a fine-grained understanding of the human interaction process, it is intuitive to think of modeling the implicit behavior sequence as a whole, which requires taking into account behavior-behavior relations. A Markov model can be applied in this situation as it accounts for both the current behavior and its predecessor. To the best of our knowledge, the Markov model has not yet been widely applied to analyze HRI systems, but it is frequently used in other domains. For example, using Markovian analysis, Chapman (1981) identified nine hidden search states in a behavioral pattern for web search behaviors. Chen and Cooper (2002) used the Markov model to analyze the patterns of Web-based library catalog browsing.

However, the Markov approach only attempts to model and interpret two consecutive behaviors at a time, which cannot directly reflect latent human cognition patterns. To overcome this issue, previous studies (Boussemart and Cummings, 2008; Yue et al., 2014) tried to model human interactions at the hidden cognitive state level, at which HMM is often adopted. Yue et al. (2014) assumed that user behaviors are driven by hidden cognitive states instead of being directly influenced by the prior interactions. Therefore, by using HMM, researchers can bridge hidden cognitive states with observed actions in one unified framework.

2.5. Hidden Markov Model (HMM)

When an operator makes choices among alternatives, the observed behaviors simply represent the adopted actions; however, similar actions may result from a variety of intentions. Highly probable actions may not best represent the user's intentions, whereas improbable events may convey more insights into operators' true internal (cognitive) states. Conventional approaches evaluate interactions and performance through the accumulated results (e.g., number of targets found) that merely reflect the operators' adopted behaviors, and may fail to examine intentions or cognitive strategies, which prompted us to perform a holistic evaluation on the intermediated behaviors.

To better model human supervisory control processes, HMM (Baum et al., 2011) was applied to examine operators' supervisory processes under different queuing approaches and system reliabilities to discover the variables influencing operators' cognitive states as well as their behavioral patterns. HMM is a well-established machine learning method that has been shown to be useful in modeling human behaviors and examining unobservable human intentions in a wide range of application domains. For example, it has been used for modeling astronaut supervisory monitoring behaviors (Hayashi et al., 2005) and web search processes (Xie and Joo, 2010; Yue et al., 2014). However, little attention has been paid to using the HMM approach in the HRI field.

HMM analysis provides advantages over conventional approaches by making the context surrounding human supervisory control explicit and aiding in the interpretation of unobservable human intentions. HMM assumes that there are several hidden states (namely, hidden user intentions) that govern the presence or absence of certain user interactions. While modeling user behaviors, HMM employs a two-layer model, in which the *hidden state layer* reflects the user's cognitive states, while the *observed action layer* represents the sequence of user actions. The hidden layer can be inferred from observed interactions, using the Baum-Welch algorithm (Baum et al., 2011).

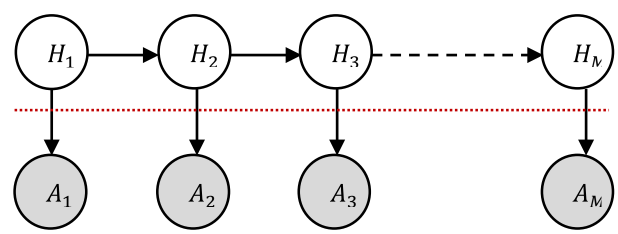

Figure 1. An illustration of Hidden Markov Model.

An illustration of HMM is provided in Figure 1. HMM assumes a sequence of *user behaviors from A_1 to A_M*, and a sequence of *hidden states from H_1 to H_M*. Here, M stands for the total number of human behaviors in one supervisory control process. Each behavior is supposed to be generated by one corresponding hidden state; however, different behaviors can be generated by the same hidden state with different probabilities. The hidden state sequence results in a

Markov Chain. A HMM model has several parameters, including the number of hidden states, the transition probabilities among any two hidden states, and the emission probability from one state to any of the behaviors. In this paper, we will follow this line of work by adopting the HMM for behavior sequence modeling and assessment in HRI domain.

3. Methods

To examine human attention allocation in multi-robot teams, urban search and rescue (USAR) missions were used in our study along with different types of scheduling displays (Figure 2 and Figure 4). The USAR mission is composed of human operator(s) and robotic agents, where an operator has to perform supervisory control of multiple robots and interact with them to explore the environments and execute the search and rescue missions. The USAR robots are capable to perform some basic tasks, such as path plan or re-plan; however, due to the environmental complexity, the robots may be unable to sense and avoid all the potential risks (e.g., bump into a furniture and get tangled). An operator must monitor the robots' statuses and interact with each as needed.

An earlier study (Chien et al., 2011) found that HRI performance can be improved by appropriately directing the operator's attention to robots in need of interaction. When robot self-reflection (Scheutz and Kramer, 2007) is used to identify a need for interaction with an operator, the resulting HRI forms a queuing system, in which the operator acts as a server to process the robot requests. To understand the effectiveness of different attention direction approaches, two types of queuing mechanisms were used to schedule operator attention in this paper:

1) Open-queue: showing the entire queue with the current status for each robot (Figure 2). This queuing mechanism gives operators an overview of all robots' states and provides color cues to differentiate the normal and abnormal status of robots along with the type of experienced failure.

2) SJF-queue: showing a single robot's request at a time based on the shortest-job-first discipline (Figure 4). This mechanism prioritizes the robot failure requests and displays the failure requiring the least effort to repair (i.e., the suggested robot can be repaired quickly). Although an operator could resolve more robots' failures in a limited time through this approach, due to the nature of a forced-queue scheme, the operator must follow the system suggestion to resolve the current prioritized request in order to proceed the next task, which provides little flexibility for the operator in handling the robots' requests.

Participants' cognitive strategies and reliance behaviors may significantly depend on the system reliability. Since guaranteeing perfect automation is unrealistic, to examine the effects of system reliability, two levels of automation aids, high (90%) vs. low (50%), were simulated in addition to the two queuing approaches. For example, in the low reliability condition, half of the robots' failures were misdiagnosed and were not reported to the operator. Additionally, HMM was adopted to further analyze the participants' cognitive intentions and decision-making strategies among the experimental setups.

3.1 Testbed Systems

Urban search and rescue simulation (USARSim; Lewis et al., 2007), a high-fidelity robotic simulation, was used in our study to simulate USAR missions, featuring USAR robots and environments. USARSim supports human multi-robot coordination by accurately rendering user interface elements and representing robot automation and its remote environment, which link the operator's awareness with the robot's behaviors.

Multi-robot control system (MrCS; Carpin et al., 2007), a multi-robot control infrastructure, was also included in our study to provide a user interface to control and display multiple robots simulated in USARSim. MrCS provides tools to control robots in the simulation, displaying multiple camera and laser output, and supporting inter-robot communication.

USARSim and MrCS were used in our study to simulate a USAR foraging task, in which an operator controlled multi-robot teams to explore the environments, detect the presence of victims, and locate the victims on the map.

Figure 2. MrCS display in Open-queue: showing current conditions of all robots in the status panel (left-most window).

Figure 2 shows the MrCS user interface in the Open-queue condition. Thumbnails of robot camera feeds are shown on the top, which display each robot's current view. Current locations and paths of the robots are shown on the Map window (middle) which allows operators to mark the position of victims. The red dots shown on the Map window are the victim marks that placed by a participant. A manually controlled panel in the bottom right allows teleoperation and camera pan and tilt. The status panel (left) for the Open-queue condition shows the current status for each robot and briefly summarizes any problems using differently colored indicators (Figure 3).

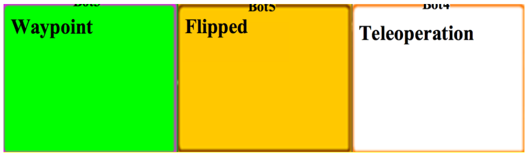

Figure 3. Status panel: Green color represents a robot is working appropriately; yellow color represents a robot is encountering problems; white color represents a robot is under manually controlled.

Green tile indicates that the robot is in autonomous condition and functioning safely; yellow tile indicates an abnormal condition, such as being stuck at a corner. When a robot is manually controlled, its tile turns white. An operator has several ways to select a robot to control, from the status panel, camera thumbnail, or map window. Once a robot is selected, its camera view is also presented in the video of interest (middle right), which provides a larger display to help operators further examine the images.

Figure 4. MrCS display in SJF-queue: showing a single alarm, by following the first-in-first-out or shortest-job-first principle respectively, in the status panel (left-most window).

Figure 4 shows the status window (left) for the SJF-queue condition in which only one robot in an abnormal state is presented at a time. Additional alarms can only be reviewed after the presenting problem is resolved. To avoid "clogging" the status window with an unrecoverable failure, operators have an option to use the "Dead button" (bottom left, Figure 2 and Figure 4). Once switched off, the robot will stop reporting and no longer be scheduled.

3.2. Primary Task: Victim Detection

The main goal of this study is to help an operator to efficiently detect victims in the multitasking situations. Through the system, once an operator notices a victim appearing in a thumbnail, a complex sequence of actions for the victim detection task is initiated. The operator first identifies the robot detecting a victim and selects it in order to see the camera view in a larger window (video of interest in Figure 2). After the operator has successfully selected a robot, the next step is to locate it on the map by matching each robot's unique border color or numerical label. Then, the operator must determine the orientation of the robot and its camera using cues such as prior direction of motion and matching surroundings between camera and map views. To gain this information, the operator may choose to teleoperate (i.e., manually control) the selected robot to locate it on the map and determine its orientation by observing the direction of movement. The operator must estimate the victim's location on the map corresponding to an image of the victim in the camera view, and then place a red dot on the map window to represent a victim's location (as the red dot shown in Figure 2 and Figure 4). If "another" victim is marked nearby, the operator must consider whether the current victim has already been recorded on the map to prevent missing or duplicate marks. In additional, a number of victims are evenly distributed in the environment and are simulated as paralyzed patients, in which the victims are unable to move and the robots can detect the victims all the time.

3.3. Secondary Task: Failure Resolved

The secondary task of this study is to resolve robot failures. An operator has to identify and select the failed robot, then teleoperate it to its next predefined waypoint where the automation can be resumed. To simulate a real robotic system, the simulated Pioneer P3-AT robot equips with the similar accessories and sensors as a real P3-AT robot, including laser sensor, color sensor, gyroscopic sensor, video camera, navigation package, global positioning system (GPS), and wireless Ethernet communications. These sensors are designed for exploring the environments, collecting surrounding data and detecting the robot's current state. As the USAR tasks often occurred in the hazard situations, the design of the multiple sensors can not only overcome the tough environments but also compensate the potential system failures caused by the risky conditions. For example, while the video camera fails to provide the instant environmental information, the operator can refer to the GPS to regain the robot's current location.

TABLE I. THREE TYPES OF FAILURES OCCURRED IN THE STUDY

Failure	**Description**
Teleoperation Lagged	Robot executed operator's command with 2~3 seconds delay
Camera Sensor Failed	Robot's video feed will be frozen right before the failure happened
Map Viewer Failed	Robot's position on the map viewer will be unable to update

Recoverable failures were categorized into 3 major types (Table I), based on the data for commonly occurring on-field repairable failures for the Pioneer P3-AT (Carlson et al., 2004). Two of these, camera and map failures, involve loss of display due to communication difficulties. Teleoperation lag is a control problem identified by Sheridan (1993) and determined to significantly degrade operator performance.

In this study, to resolve a robot's failure, the operator needed to manually guide the robot from its current location to the next waypoint. Because each of the failure types imposed different difficulties for recovery, they took varying amounts of time to resolve. In order to estimate a typical resolution duration for different failures, a pretest using 10 participants was conducted. The resulting durations were adopted from our prior study (Chien et al., 2012a), in which the camera failure was the easiest to overcome and the loss of map indication proved to be the lengthiest failure to repair, with teleoperation delay falling in the middle. This ordering of estimated interaction times allowed failures to be presented to the operator in the SJF-queue following a shortest-job-first discipline, known to maximize throughput (Garey et al., 1976). In addition, to fulfill our experimental designs and satisfy the SJF methods, only one type of a failure will be injected to a robot at one time (e.g., teleoperation lagged and camera sensor failed will not be occurred to a robot simultaneously).

3.4. Experimental Conditions

The selected USAR environment was an office-like hall with many rooms full of obstacles such as chairs and desks. Victims were evenly distributed throughout the environment, and robots entered the environment from different locations.

A total of six P3-AT robots were used in our study to perform the USAR task. Robots followed predefined paths of waypoints, similar to paths generated by an autonomous path planner (Chien et al., 2010) to explore the environment. All robots traveled paths of the same distance with ten visible victims and four system failures (i.e., robots' failures not detected) along each designated path. Upon reaching a pre-programmed failure waypoint, the robot experienced a failure and sent a request to the queue. The operator then needed to assume manual control to teleoperate the robot out of its predicament and on to its next waypoint where communication could be reestablished with the lost camera feed or control, and autonomous exploration resumed.

3.5. Participants and Procedure

Forty-eight student participants were recruited from the University of Pittsburgh community, a group balanced in terms of gender (average age = 26.53). None had prior experience with robot control, although most were frequent computer users. A 2x2 between-subject design was applied to the study, in which each participant only experienced one of the queuing displays (Open-queue or SJF-queue) along with one of the reliability levels (high-90% or low-50%).

Participants first read standard instructions about the experimental conditions. Participants were instructed that their primary task was to detect and mark as many victims as possible and their secondary task was to resolve robot failures. Additionally, they were also informed that a cognitive queue was used in managing the robot failure tasks, but that the queuing reliability was not perfectly reliable. In the following 15-minute training sessions, participants practiced control operations by resolving failures, three times for each type. Participants were encouraged to find and mark at least one victim in the training environment under the guidance of the study conductor. After the training session, participants began the 15-minute experimental session controlling 6 robots in the assigned condition. Participants had been told the main task was to locate victims via detecting and that resolving robot failures was a secondary task. At the conclusion of the session, participants were asked to complete the NASA-TLX workload survey (Hart and Staveland, 1988).

3.6. Evaluation: User Behavior Analysis using Hidden Markov Model (HMM)

To provide a deeper understanding of human interactions on different attentional scheduling conditions, this study examined the users' decision-making processes in visual search and scrutinized their hidden intentions when performing USAR tasks. Latent user intentions were automatically detected through HMM, a two-layer (including hidden layer and observed layer) unsupervised machine learning model that assumed the observed layer was generated from the hidden layer. The hidden layer included a set of hidden states, whereas the observed layer consisted of observed user behaviors. Prior research suggested, with a small number of tweaks, HMM can quickly learn the users' hidden states by using the Baum-Welch algorithm (Baum et al., 2011).

To learn the hidden states and corresponding parameters, we first need to specify the number of hidden states, which is a non-trivial task because of the lack of ground-truth. A complex model with a large number of hidden states may describe user interactions more accurately and specifically for one dataset, but it may be unable to predict other datasets under different task contexts. In HMM model selection, an information criterion such as Akaike information criterion (AIC; Akaike, 1974) or Bayesian information criterion (BIC; Mcquarrie, 1998) is adopted to avoid over-fitting. For this study, we chose to use the BIC score to determine the optimal number of hidden states for the HMM, because the BIC score accounts for the sample size (Yue et al., 2014). There are two important output matrices for a HMM: *Emission Probability* (also known as output probabilities) represents the distributions of the observed interactions from a specific state; *Transition Probability* shows the probability of transferring from one hidden state to another. Both of these measures were adopted in this paper.

4. Results

Data were analyzed using a 2x2 between-subject ANOVA with scheduling mechanisms (Open-queue vs. SJF-queue) and reliability levels (high-90% vs. low-50%) to determine the differences in operators' performance. The following measurements (Table II) were adopted in our analysis:

Two types of analyses were adopted: 1) the conventional performance analysis, and 2) the HMM analysis. The conventional performance analysis examined the overall performance in the primary and secondary tasks, and the

TABLE II. MEASUREMENT SCALES AND ITS DEFINITION AND CONCEPT

Measure	Definition & Concept
Conventional Performance Analysis	
Total Detected Victims	The number of victims detected by the robots while exploring the environment, which results in an operator's opportunity to detect the victim appearances
Victim Finding Rates	*Number of correctively marked victims* divided by *Total detected victims*, which indicates an operator's performance in the primary task
Victim Missing Rates	*Number of missing victims* divided by *Total detected victims*, which represents an operator's SA in the primary task
Failures Resolved	The amount of robots' failures resolved by an operator, which shows an operator's performance in the secondary task
Area Explored	The total distance travelled by the robots, where larger distance leads to better opportunities to find more victims
Workload Survey	An operator's experienced workload is evaluated by the NASA-TLX workload survey, where task performance may decline when the operator perceives too high or too low workload
Hidden Markov Model Analysis	
Emission Probability	Counting the frequency that a specific interaction is generated by a cognitive state
Transition Probability	Computing the probability of transferring from one cognitive state to another

subjective perceived workload. However, these examinations considered only the accumulated results (e.g., number of victims found) and failed to reveal an operator's hidden cognitive intentions. The HMM analysis was therefore included in our analysis to further access the operator's cognitive strategies via the emission and transition probabilities. A small portion of the preliminary results of the conventional performance analysis (number of victim detections and failures resolved, and workload scores) was presented in (Chien et al., 2013, 2012c); however, this paper adopted more precise measures (e.g., victim finding and missing rates) to determine the differences and applied the HMM approach to scrutinize the cognitive variances.

4.1. Conventional Performance Analysis

4.1.1. Victim Detection (Primary Task)

Since the number of marked and unmarked victims are related to the existing of victim appearances, the number of detected victims was therefore first examined. The results showed a main effect for reliability conditions ($F_{1,44}$=4.888, p=.032) and queue mechanisms ($F_{1,44}$=5.426, p=.024), where more victims were detected under the high reliability and in the Open-queue condition (as shown in Figure 5). A pair-wise T-test showed that more victims were detected in the Open-queue method than in the SJF-queue condition (p=.041) under high reliability; as well as more victim targets were sensed in the high reliability than low reliability condition (p=.059) under the Open-queue approach.

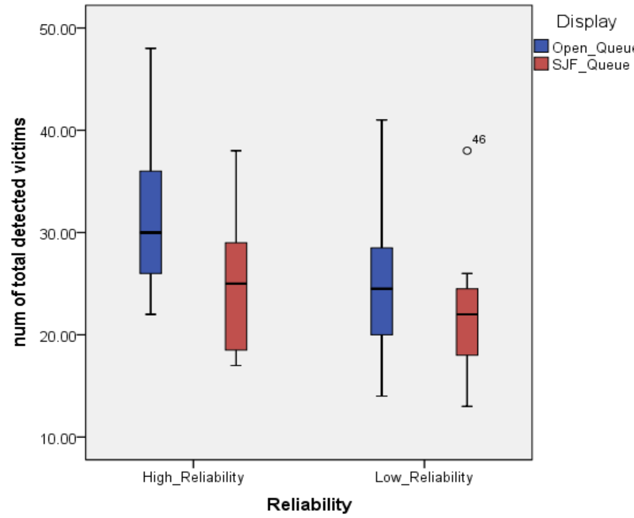

Figure 5. Number of total detected victims.

To better examine the relationship between the correct victim marks and total detected victims, an adjusted measure, *victim finding rates,* was used and computed by the number of correct victim marks divided by the total detected victims. Significantly higher victim finding rates were observed in the low reliability condition ($F_{1,44}$=5.976, p=.019), as shown in Figure 6. A pair-wise T-test further revealed that, under the Open-queue condition, more victims were successfully marked in the low reliability than in high reliability condition (p=.051); however, the same effect was not observed in the SJF-queue approach.

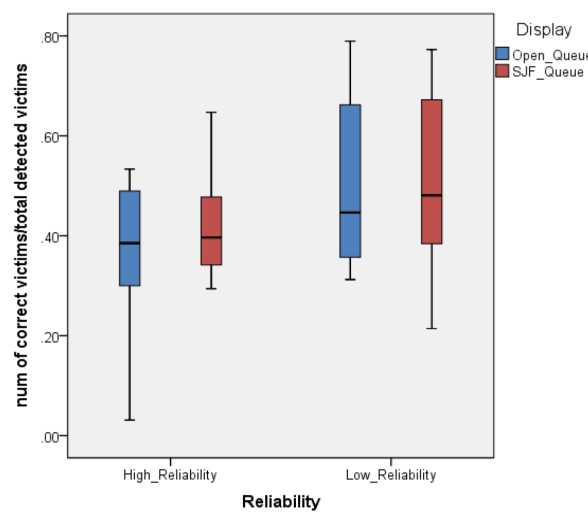

Figure 6. Victim finding rates.

An unmarked victim (i.e., missed target) can result from insufficient SA that should be addressed in the victim detecting process. An unmarked victim was defined as a victim appearing in a robot's camera without being located by the operator. Another adjusted measure, *victim missing rates*, was calculated by the number of unmarked victims divided by the total detected victims. The results revealed a main effect for reliability conditions ($F_{1,44}$=5.976, p=.019), in which higher victim missing rates were found under high reliability condition (as shown in Figure 7). The results of pair-wise T-test revealed that, in the Open-queue condition, more victims were missed in the high reliability than low reliability condition (p=.051). No statistical effect was found in the SJF-queue condition between the reliability levels.

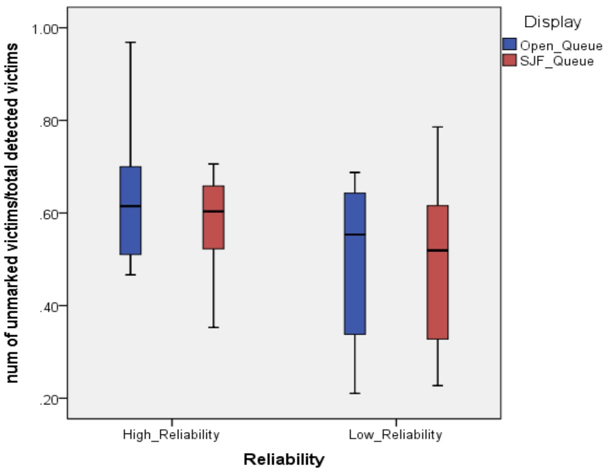

Figure 7. Victim missing rates.

4.1.2. Failure Resolved (Secondary Task)

To examine the effects of unreliable automation, pre-programmed system failures were injected along a robot's route. When a robotic agent encountered the predesigned failures, the robot sent a request for further interaction and waited for the operator's assistance. The results showed that significantly more failures were resolved under high reliability condition ($F_{1,44}$=6.057, p=.018), as shown in Figure 8. A pair-wise T-test revealed that, under the Open-queue approach, participants resolved more robot failures in higher reliability condition (p=.055); however, similar results were found in the SJF-queue regardless of the reliability levels.

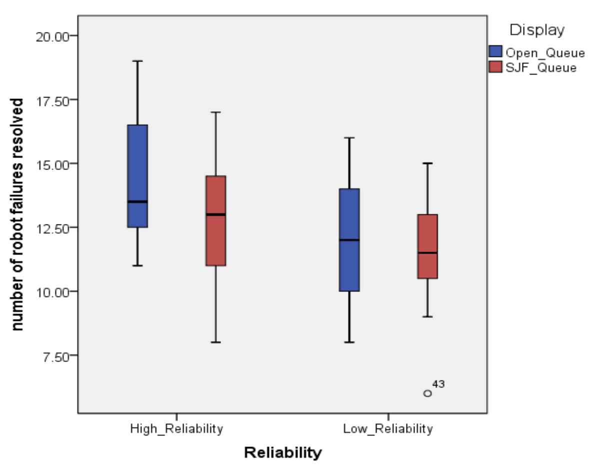

Figure 8. Number of robot failures resolved.

4.1.3. Area Explored

Exploring larger areas could result in greater opportunities to detect more victims. The results showed marginal differences in the queue scheme ($F_{1,44}$=2.844, p=.099), which suggested that when an operator interacted with the robotic agents via the Open-queue approach, the robots were able to travel longer distances; however, this effect was not observed in the lower reliability level (as shown in Figure 9).

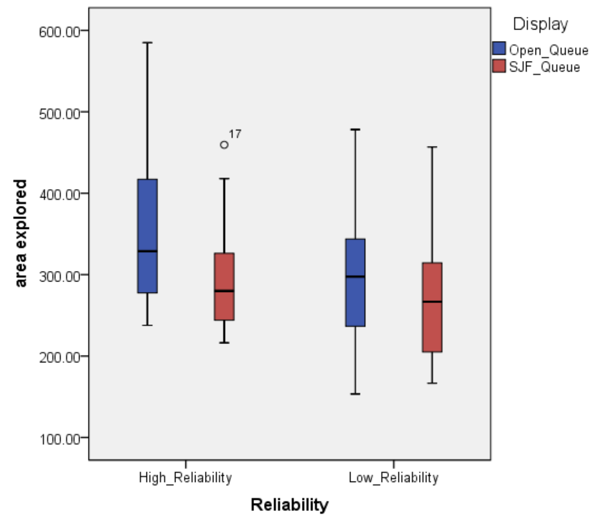

Figure 9. Area explored.

4.1.4. Interactive Behaviors between Queue and Camera

The participants had multiple ways to interact with the robotic agents (i.e. selecting from the robot cameras, from the cognitive queuing assistant, or from the map window). The results revealed that the selection behaviors were significantly influenced by the queue schemes ($F_{1,44}$=20.867, p<.001), in which the operators were inclined to interact with the robots through the provided cognitive queue in the Open-queue condition (as shown in Figure 10). Neither interactions nor reliability levels were found to be statistically significant.

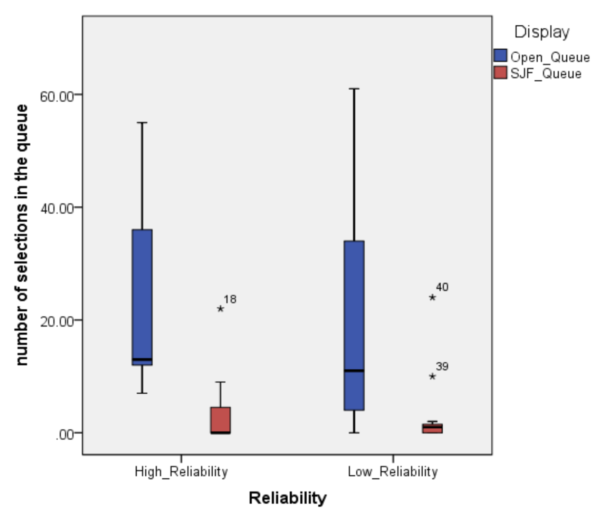

Figure 10. Number of selections in the cognitive queue.

As shown in Figure 11, the results showed significant differences in reliability conditions ($F_{1,44}$=3.450, *p*=.070) and queuing displays ($F_{1,44}$=4.307, *p*=.044), in which the results indicated that operators tended to interact with the robots via the camera panels under low reliability level and in the SJF-queue condition. A pair-wise T-test further identified decreased reliability in the Open-queue condition significantly increased the use of robot cameras (*p*=.043); however, this effect was not observed in the SJF-queue.

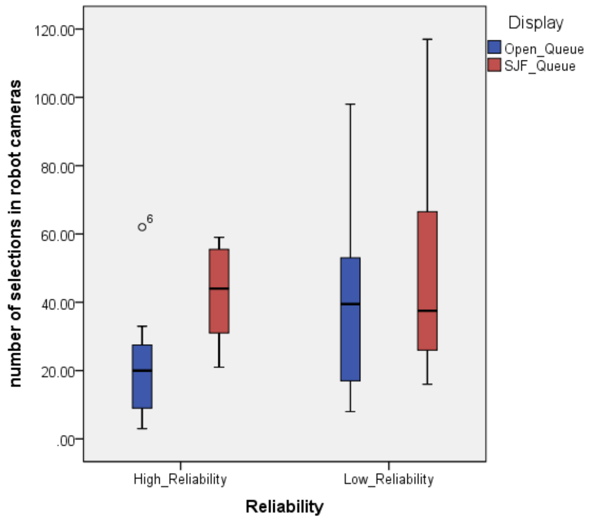

Figure 11. Number of selections in robot cameras.

4.1.5. Perceived Workload

The NASA-TLX instrument was used to evaluate an operator's perceived workload in performing the USAR task. The results showed a significant interaction between the reliability levels and queue types ($F_{1,44}$=3.879, *p*=.055), in which the highest workload was reported under high system reliability in the Open-queue condition, and the lowest workload score was reported under high reliability condition in the SJF-queue scheme (as shown in Figure 12). A pair-wise T-test further revealed that under higher system reliability, operators perceived heavier workloads in the Open-queue than SJF-queue condition (*p*=.010). To investigate the influence related to the prescriptive aids in the SJF-queue scheme, the frustration scale was analyzed separately. The results showed that, under high reliability, higher frustration scores were reported in the Open-queue than SJF-queue situation (*p*=.062).

The analysis above measured the participants' overall performance while interacting with the cognitive queuing assistants to prioritize robots' requests under various conditions. However, these measures failed to reveal the underlying factors affecting operators' cognitive states and decision-making strategies while performing supervisory control over multiple robots in multitasking environments. The deficiency of cognitive resources has been a longstanding problem in multitasking conditions, in which the operators themselves may not be aware that insufficient resources increase the difficulty of reflecting on the problem. As a result, identifying the deficiency in provided cognitive queuing aids requires a fine-grained approach to further evaluate the interaction between human operators and cognitive assistants. Therefore, a machine learning approach, HMM, was adopted to examine the operators' cognitive intentions.

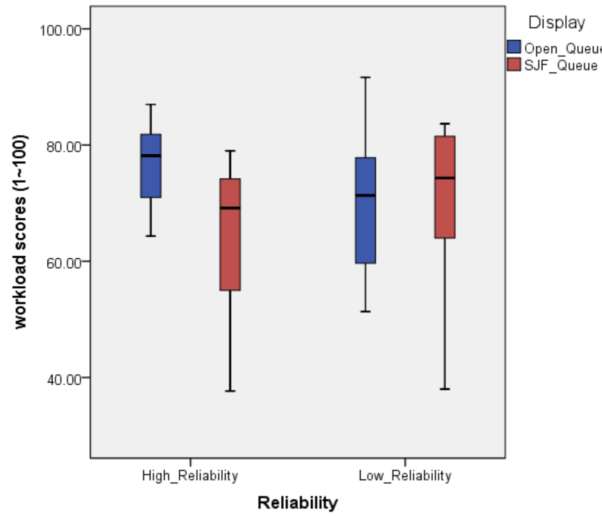

Figure 12. Perceived Workload.

4.2. Hidden Markov Model (HMM) Analysis

A HMM requires a list of sequentially observed user interactions as input. The interactions used in this study were obtained through two test-bed systems, USARSim and MrCS, by recording *users' click actions*. Based on users' click actions, we sorted the logged actions into six categories, including status panel, camera, map, teleop, auto, and victim (details are included in Table III). An operator can select a robot to control from either its thumbnail (indicated as Camera in table III), its icon on the map window (Map), or its legend on the cognitive assistant (Queue). The victim detection task is completed by placing a mark on the map window (Victim). In the failure recovery task, an operator first selects a failed robot and manually controls the robot to the next predefined waypoint (Manual), then completes the task by returning the robot to the autonomous mode (Auto).

TABLE III. USER INTERACTION CATEGORIZATION

Interaction	Description
Queue	A user checked the cognitive assistant (coined as status panel in Figure 2 and Figure 4) and selected a robot from the queue
Camera	A user clicked on a camera to select a robot
Map	A user selected a robot in the map window
Manual	A user manually controlled a robot to solve the robot failures or to locate a victim
Auto	A user clicked on the auto button to set a robot to the autonomous mode
Victim	A user added/deleted a victim mark on the map

Probabilities and transitions among the retrieved hidden states reveal a great deal about an operator's strategies and interactions with the system aids. For example, the probability of the use (or disuse) of the provided cognitive assistant (i.e., Queue) provides evidence for its role in influencing operators' internal cognitive states, whereas the resulting transitions are likely to involve robot failures that have been resolved.

4.2.1. Open-queue Model

Four hidden states were identified in the high reliability condition and were labeled based on the emission probability, which represents the probability of the observed interactions from a cognitive state (Table IV, emission probabilities lower than 0.10 were omitted for legibility purposes). The first hidden state had a high probability (62%) of generating an interaction with Queue (defined in Table IV); we therefore named it HQ. Based on the same naming schema, we noted the rest of interactions as HC (Camera), HA (Auto), and HM (Manual). The results revealed that, in the Open-queue condition, operators tended to interact with robots through the camera or queue panels (HC and HQ states, respectively) rather than from the map window, leaving the Map state out of the model. Additionally, the Victim state was observed across HQ, HC, HA, and HM states, but never dominated in any of the conditions. Therefore, due to its low probability, the Victim state was not included in the model.

TABLE IV. EMISSION PROBABILITIES IN **OPEN-QUEUE** under the **High Reliability** CONDITION

OPEN HR	QUEUE	CAMERA	MAP	MANUAL	AUTO	VICTIM
HQ	*0.62*	0.12				0.17
HC		*0.75*				0.18
HA					*0.79*	0.20
HM				*0.94*		

Transitions among these four hidden states were plotted in Figure 13 (transition probabilities lower than 0.10 were also omitted for legibility purposes). A pattern of high transition probability was observed in HQ→HM→HA, when an operator resolved a robot request from the queue (HQ) and manually drove the robot from the failure point to the next predefined waypoint (HM). Upon reaching the waypoint, the robot resumed the autonomous mode (HA); then the operator selected another robot from the queue to fulfill the robot's requests (HA→HQ).

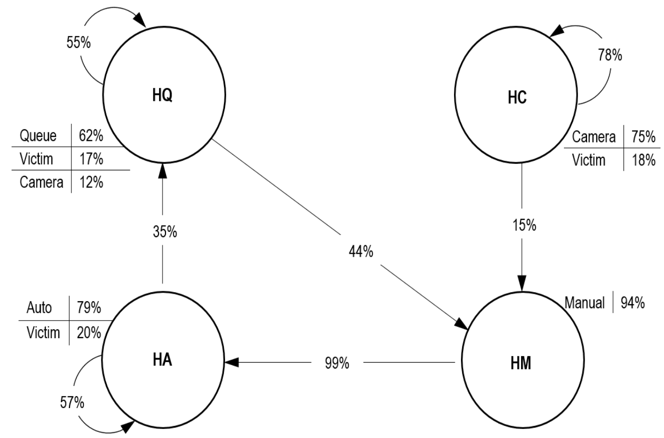

Figure 13. Transition probabilities of hidden states in **Open-queue** under the **high reliability** condition.

Another four hidden states model was found in the low reliability condition (shown in Table V), which was similar to the retrieved structures in the high reliability condition. The HM, HA, HC, and HQ states significantly involved the interactions of Manual, Auto, Camera, and Queue, respectively.

TABLE V. EMISSION PROBABILITIES IN **OPEN-QUEUE** under the **Low Reliability** CONDITION

OPEN LR	QUEUE	CAMERA	MAP	MANUAL	AUTO	VICTIM
HM		0.05		*0.79*		0.14
HA					*0.72*	0.23
HC		*0.84*				
HQ	*0.80*		0.10			

The transition probabilities were visualized in Figure 14 and the transition pattern (HQ→HM→HA) was again observed. However, while interacting with unreliable system aids, operators exhibited more complex behavioral patterns. When compared to the high reliability condition, decreasing system reliability generates more links (HM→HC: 21%; HA→HC: 30%) and transition pattern (HM→HA→HC) to the Camera state, which did not exist in the high reliability condition.

To examine the potential differences in emission and transition probabilities between the high and low reliabilities in the Open-queue conditions, pair-wise T-tests were conducted. The results are summarized in Table VI. The comparisons in emission and transition probabilities indicated that operators relied more on the cameras than the provided cognitive queue under the low reliability condition.

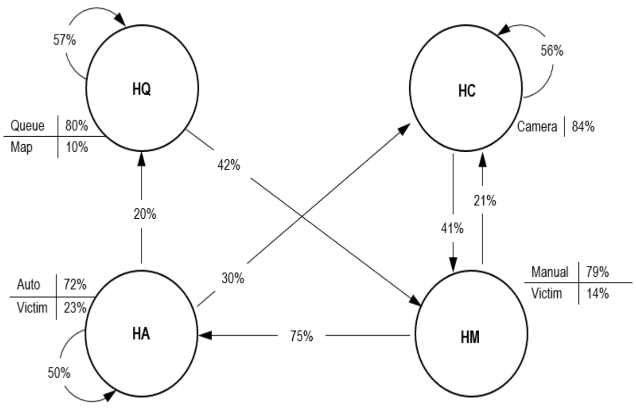

Figure 14. Transition probabilities of hidden states in **Open-queue** under the **low reliability** condition.

TABLE VI. T-TEST ANALYSIS IN EMISSION AND TRANSITION PROBABILITIES BETWEEN **HIGH AND LOW RELIABILITY** CONDITIONS IN **OPEN-QUEUE**

Emission Probability	
States	Post-hoc
Queue (HQ)	HR>LR, *p*=.050
Camera (HC)	LR>HR, *p*=.011
Manual (HM)	LR>HR, *p*=.035
Transition Probability	
States	Post-hoc
HQ→HM	HR>LR, *p*=.002
HA→HQ	HR>LR, *p*<.001
HC→HM	LR>HR, *p*<.001
HA→HC	LR>HR, *p*<.001
HM→HC	LR>HR, *p*<.001

4.2.2. SJF-queue

The emission probability matrices (table VII) revealed a four hidden states model in the SJF-queue under the high reliability condition. When compared to the SJF with Open conditions, the Queue state had low probability and was therefore excluded from the model. However, a Victim state was identified as a dominant state in the SJF condition, while it had little effect in the Open condition. The results revealed that operators were less likely to interact with the provided cognitive assistant (i.e., Queue) in the forced-queue SJF condition.

Two major patterns were observed in the transition probabilities in the SJF-queue condition (Figure 15), HM→HA→HC and HM→HV→HA→HC. These patterns indicated that operators allocated more attention to interacting with the cameras while performing the tasks. For

TABLE VII. EMISSION PROBABILITIES IN **SJF-QUEUE** under the **High Reliability** condition

SJF HR	**QUEUE**	**CAMERA**	**MAP**	**MANUAL**	**AUTO**	**VICTIM**
HC		*0.79*				
HM				*0.88*		
HV			0.11			*0.87*
HA					*0.93*	

example, an operator may first manually drive the robot to (re)gain necessary awareness (HM) and then switch the robot back to autonomous mode (HA). From that point, the operator used the cameras (HC) to monitor overall statuses, including marking the location of victims and solving the robot failures. When a victim appeared on a robot camera, an operator manually controlled robots (HC→HM) to gain the victim's location in order to increase the accuracy of a victim mark (HV). Once a mark had been placed, the robots were set to autonomous mode (HA) and the operator allocated her attention to the cameras (HC) to again perform supervisory control of the robot teams and maintain SA. If another victim appeared in a robot's camera, the above procedures were repeated.

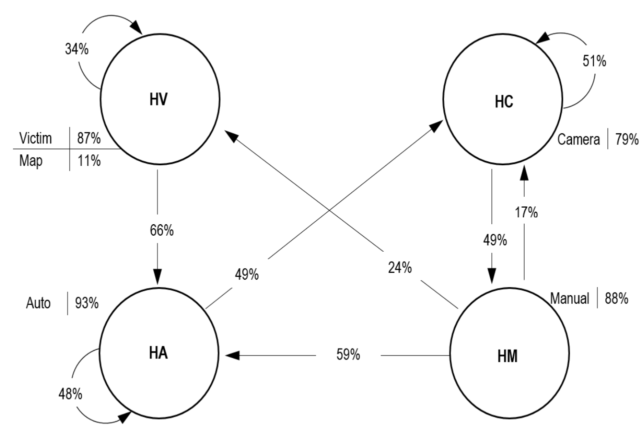

Figure 15. Transition probabilities of hidden states in **SJF-queue** under the **high reliability** condition.

Identical models were retrieved from the emission probabilities matrices in SJF-queue under the low reliability condition. Table VIII includes emission distributions among the hidden states. As a result, the Map and Queue states were of little use and therefore are absent from the model.

The identical transition patterns were found in the SJF-queue under the low reliability condition (Figure 16). Further analyses (T-test) were conducted to identify the differences in emission and transition probabilities in SJF conditions with different reliability levels. However, no statistical difference was observed.

TABLE VIII. EMISSION PROBABILITIES IN **SJF-QUEUE** under the **Low Reliability** CONDITION

SJF LR	**QUEUE**	**CAMERA**	**MAP**	**MANUAL**	**AUTO**	**VICTIM**
HM				*0.87*		
HV		0.13				*0.78*
HC		*0.86*				
HA					*0.91*	

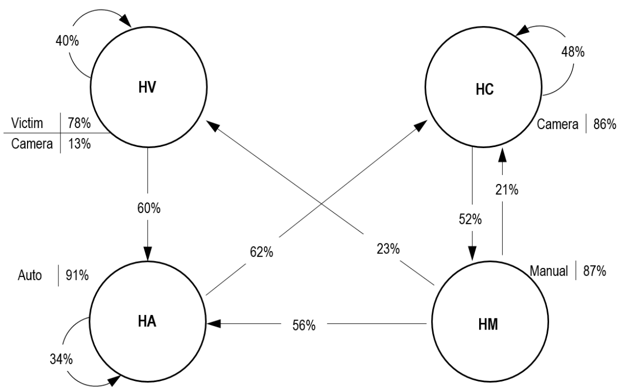

Figure 16. Transition probabilities of hidden states in **SJF-queue** under the **low reliability** condition.

5. DISCUSSION

Using limited cognitive resources effectively is critical in human multi-robot interaction, in which operators must efficiently allocate their attention to urgent events and simultaneously selectively filter out any unnecessary information (Kirlik, 1993). Prior studies (Chien et al., 2012b; Crandall et al., 2005; Kozima and Yano, 2004; Yan et al., 2013) suggested that robot self-reflection can enhance the performance of human-robot teams, which allows operators to focus on important tasks rather than shifting attention to interact with robots sequentially in a round-robin fashion. This study further examines the effect of unreliable automation (high-90% vs. low-50%) in a human multi-robot control system along with two types of queuing principles (Open vs. SJF) for scheduling the operator's attention. The Open-queue displays the current status for each robot so that an operator can choose which robots to assist in a self-paced fashion; while the SJF-queue only provides an alarm by following the shortest-job-first discipline to direct an operator to service the highest priority task. In terms of the reliability conditions, under low system reliability, only half of the robot failure requests are reported to the cognitive queuing aids and the other failures are excluded from the queue.

5.1. System reliability in Queuing Aids

Although the measures of the *total number of detected victims* favored the high reliability condition, *victim missing rates* were also increased under high reliability level. In other words, better performance in *victim finding rates* was found under the low system reliability. The result may be caused by an insufficient attention allocation strategy. Under the high system reliability, as most of the robots' failures were accurately reported through the queuing aids, the operators were capable of maintaining adequate SA in robots' statuses and efficiently allocating attention to fulfill robots' requests. As a result, operators may spend more resources on assisting robots' failures rather than devoting sufficient attention to monitoring victim appearances. This attentional strategy led to the robots having better chances to remain in the autonomous mode (rather than in the failed status and waiting for the operator's assistance) to explore the environments and therefore have greater opportunities to detect potential victims; however, this attentional approach resulted in suboptimal performance in the primary task, locating and marking the victim appearances. Our results confirmed these assumptions. Participants resolved more robot failures and experienced higher *victim missing rates* in the high system reliability; whereas higher *victim finding rates* and fewer *robot failures* were accomplished under the low reliability condition. Since half of the robot failures were not detected under the low system reliability, participants could focus their attention on detecting the potential victims, which resulted in higher response rates for victim appearance (i.e., higher victim finding rates).

In addition, the system's reliability greatly influenced operators' interactive behaviors with the robots. More *camera selections* were observed under low system reliability, indicating that the unreliable system led the operators to *actively* supervise robot statuses and system performance through the cameras, rather than *passively* received notifications from the provided cognitive queuing assistant. As the operators devoted more attentional resources to the cameras, the behavioral changes also increased opportunities for them to detect the victims' appearances. The aforementioned results partially confirmed our first hypothesis, in which higher reliability levels increased the overall number of detected victims and area explored but did not necessarily contribute to better victim finding rates.

5.2. Queuing mechanisms

Significantly higher numbers of *total detected victims* and larger *areas explored* were found in the Open-queue than the SJF-queue condition. Our second hypothesis was based on Garey's (1976) findings that suggested the SJF scheme can effectively enhance task performance. However, our results showed that the SJF-queue scheme failed to outperform the Open-queue approach across all the experimental setups, which negated our second hypothesis. The Open-queue approach presented all robots' conditions and used different colors to indicate robots' current situations. The frequent updates of color cues seemed to drastically attract operators' attention and encouraged them to respond robots' requests in a timely manner. The situation was confirmed by the differences in the interactive behaviors between queuing aids and robot cameras. As shown in Figure 10 and Figure 11, in the SJF-queue approach, little attention was devoted to the provided cognitive assistant (i.e., queue) and operators tended to interact with robots through the cameras, whereas contrary results were found in the Open-queue condition (i.e., operators relied more on the queuing assistant in the Open-queue). In the Open-queue condition, operators were not required to follow the system recommendation to interact with a specified robot request. However, under the self-paced interactions, operators may devote additional resources to sort the high-priority robot requests, which reserved little attentional resources for monitoring victims' appearances. Because of the ineffective scheduling strategy in the Open-queue condition, showing all robots statuses along with failure requests may distract an operator's attention and lead the participant eager to solve the failed robots, instead of focusing on the victim detection task.

5.3. System reliability x Queuing mechanisms

As the insufficient attentional scheduling strategy was observed in the Open-queue scheme, increased system reliability led the operators to allocate even more attention to responding to the robots' requests, which led to the poor performance in *victim finding rates*. Therefore, the effects of system reliability were not as expected. Since most of the robot failures were reported in the Open-queue condition under high reliability, the endless robots' requests largely consumed operators' attentional resources leading to lesser attention available for the victim detection tasks. In other words, with low system reliability in Open-queue, operators had more resources to focus on the primary task. These observations were supported as the higher number of *failure resolved* and increased *victim missing rates* were both under the high reliability condition in the Open-queue; however, the effects of system reliability were not found in the SJF-queue. The differences in outcomes of *victim finding/missing rates* and *failures resolved* remained negligible between the reliability levels in the SJF conditions, which suggested that the SJF scheme can effectively help operators to achieve stable performance in the primary as well as secondary tasks regardless of the effects of unreliable system aids. Our third hypothesis surmised both queuing approaches would achieve better outcomes under the high system reliability. However, the measures of *victim finding/missing rates* favored the low reliability condition in the Open-queue, and little difference was observed between queuing reliability in the SJF-queue approach, which denied the third hypothesis.

Although securing system reliability in the Open-queue condition enhanced the performance in the failures resolved task, it failed to contribute to a better outcome in the victim detection task. The adoption of the Open-queue scheduling approach allowed operators to freely choose a robot to serve. This is particularly helpful when an operator had difficulties in complying with unreliable system aids. As observed in the Open-queue, under the low reliability level, increasing numbers of robot selections were shifted from the queuing aids to robot cameras, which showed that the interactive behaviors in the Open-queue approach were adaptable when the system aids contributed less assistance.

5.4. User perception of workload and frustration

The use of cognitive assistance may decrease operators' perceived workload in the supervisory control process. An interesting finding in the workload survey was that both the highest and lowest workload scores were reported in the high reliability conditions, where the Open-queue had the highest workload and the SJF-queue was judged as having the lowest. However, participants experienced similar workloads between the two queuing methods under low system reliability.

Since the Open-queue approach showed all robots' (normal and abnormal) conditions and continuously reported each robot's status via the color aids, participants might feel more distracted by the changes in color cues. This effect was exacerbated with the endless updates under the high reliability condition, which resulted in a higher level of perceived workload. The SJF mechanism prioritized robot requests based on the task difficulty and clustered similar types of robot failures, which reduced the decision-making time and decreased the cognitive cost to switching between recovery procedures by sharing the similar cognitive strategies among various types of failures. In other words, operators may not only take advantage of decreasing the cost of regaining SA between robots' requests, but also resolve more failures with no effort (e.g., camera failure), leading the differences of perceived workload.

Additionally, a high frustration was reported in the Open-queue condition, while the lowest score was reported in the SJF-queue method under the high reliability condition. The effects may be caused by reasons similar to those seen in the workload variances, where endless robot failure requests can generate a higher level of frustration. The above results partially confirmed the forth hypothesis, in which a lower workload and frustration were judged in the SJF-queue than the Open-queue conditions; however, this effect was only found under the high reliability condition, but it did not exist in the low reliability situation.

5.5. Hidden Markov Model

This paper applied HMM to examine human supervisory control processes in human multi-robot interactions. Although a similar four-state HMM structure was observed among the experimental conditions, the results reveled that HMM-based analysis was able to discover fundamental differences between the two experimental queuing mechanisms under two levels of system reliability, which were difficult to examine through the conventional performance analysis. For example, although the results of the primary task (victim finding/missing rates) and the secondary task (failures resolved) were similar in both the Open and SJF schemes, a Queue (HQ) state was observed in the Open-queue condition, whereas a Victim (HV) state was retrieved in the SJF-queue condition. The variances in cognitive states revealed the fundamental differences between the two queuing conditions, which suggested that

HMM could provide deeper analysis and further differentiate users' behavioral patterns as well as cognitive intentions.

The notable differences between the retrieved cognitive states (HQ vs. HV) also reflected the transition probabilities and resulting patterns. While a Victim state was generated by the SJF method, this could be that operators devoted more cognitive resources to the victim detection tasks rather than accepting the suggestions from the queue. The identical HMM structure was therefore found in the SJF-queue condition in both high and low reliability levels. That suggests that the SJF scheme was more robust regardless of the system reliability conditions. In the Open-queue condition, the cognitive Queue (HQ) state and transition pattern (HQ→HM→HA) revealed that a considerable amount of attentional resources was devoted to the subtask of monitoring robots' conditions and assisting robot failure requests, which enabled the robots to explore larger areas and detect more potential victims, leading better performance in the measure of *total victims detected* and *area explored* in the Open-queue.

Allowing operators a self-initiated series of events increased the complexity of the supervisory control processes. As shown in the Open-queue method, most of the cognitive states included at least two interactions (except HM in high reliability). In addition, different transition patterns were identified between the reliability conditions in the Open-queue (Figure 13 & 14). The post-hoc comparisons (Table VI) further proved the differences, in which decreasing reliability led the operators to divert from the cognitive queue and allocate more attention to the robots' cameras. As a result, the Queue (HQ) and Camera (HC) states were greatly influenced by the reliability conditions, in which fewer Queue transitions and more Camera transitions were found in the low reliability condition. In other words, with the decreased system reliability in the Open-queue, more transition patterns were linked to the Camera state. For example, in the Open-queue, a new transition pattern (HM→HA→HC) was only found under low reliability. This pattern was also found in the SJF-queue across the system reliability conditions. The transition differences revealed operators' adaptive behaviors while interacting with the low reliability aids, and further explained the performance variances (e.g., victim finding/missing rates and number of failure resolved).

As the identical HMM model was observed in the SJF condition and more complicated HMM structures were retrieved in the Open-queue method between the reliability levels, the results supported our last hypothesis, in which more sophisticated HMM patterns were found in the Open-queue group. These findings suggested that HMM can provide a high-level abstraction of users' intentions and identify the underlying behavioral patterns that are difficult to achieve through a conventional analysis.

6. CONCLUSION

Human multi-robot interaction is a complex process, in which human operators must continuously shift their attention between operating robotic agents and monitoring the system's status among various tasks. Prior research concludes that human operators often fail to schedule their attention to the correct events on time, which leads to suboptimal task performance. To optimize attentional resources, this study investigated two different scheduling approaches under two levels of system reliabilities.

The results confirmed that human attentional resources can be effectively scheduled and directed to emergent events rather than normal monitoring. The SJF-queue approach was capable of providing a balanced performance in both the primary and secondary tasks with a lower level of perceived workload, whereas the Open-queue scheme seemed less effective in the USAR context. However, it is unrealistic to decide which queuing mechanism is superior since different contexts require different cognitive assistance. For example, while monitoring multiple street-sweeping robots, the SJF-queue can prioritize and suggest easier tasks (e.g., camera sensor failed) for operators; whereas when supervising a team of surveillance robots, the Open-queue can be a better choice to allow an operator to choose the tasks based on the context (e.g., daytime vs. nighttime). The results also suggested that simply increasing the system reliability may not necessarily contribute to better task performance. Thus, examining how human operators deploy their cognitive resources between cognitive assistance and task contexts will be critical to enhance the overall performance.

The increased use of human-robot systems raises many societal challenges as well as research opportunities. As the modern robotic systems not only supplant the inherent task risks of human operators' safety but also optimize the benefits of technological capabilities, the rapid growth in task complexity requires more flexible system designs to enhance competitiveness. However, under the multitasking conditions, human operators may have insufficient resources to monitor and interact with multi-agent teams simultaneously. The developed SJF queuing mechanism can efficiently schedule an operator's limited cognitive resources to the needed events in a timely manner. In addition, investigating how human operators consume their attentional resources in the multitask settings is also critical to facilitate the processes of human-machine interaction. As the results demonstrated, the HMM analysis enables researchers to better understand an operator's cognitive states and intentions as well as to predict potential behaviors by elaborating on strategies and biases that may be difficult to study through conventional approaches. The user interaction measured in the present HMM analysis was obtained from the logs of the clicked behaviors in our experimental system, with no customization of the context-specific or system-specific interactive behaviors. Therefore, by following the standard process, the behavior categorization schemes and the procedures of performing a HMM are capable of being generalized to other HRI systems. Understanding the interactive process can provide researchers with useful suggestions to improve the design of cognitive assistance. We expect that the HMM approach could benefit researchers in further investigating users' cognitive needs.

Due to the experimental setup, this study only investigated the interaction between a single operator and multiple robot teams, in which only one type of the predesigned failures was injected to a robot at one time. Although the present research has been carefully conducted, it might always have some extreme situations in realistic that were excluded in this study (e.g., a complete failure of multiple sensors). In future works, we hope to examine a range of team structures (e.g., multiple operators controlling various number of intelligent agents) and system reliability (e.g., multiple sensor failures or false alarm prone vs. miss prone) combinations to develop a more robust cognitive assistant.

ACKNOWLEDGMENT

This research was supported in part by the AFOSR [FA955008-10356] and the ONR [N0001409-10680].

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