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Human-Agent Teaming for Multi-Robot Control: A Literature Review

by Jessie Y. C. Chen and Michael J. Barnes

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14. ABSTRACT
The literature on intelligent systems was reviewed in relation to the following: efficient human supervision of multiple robots; appropriate human trust in the automated systems; maintenance of human operator's situation awareness; individual differences in human-agent (H-A) interaction; and retention of human decision authority. A number of approaches, from flexible automation to autonomous agents, were reviewed and their advantages and disadvantages were discussed. Also discussed were two key human performance issues (trust and situation awareness) related to H-A teaming for multi-robot control and some promising user interface design solutions to address these issues. Some key individual differences factors (operator spatial ability, attentional control ability, and gaming experience) were identified that may impact H-A teaming in the context of robotics control.

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human-robot interaction, intelligent agent, automation, trust, situation awareness, individual differences

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1. Introduction

Robots and other unmanned systems have been increasingly used for various tasks, including transportation safety, space exploration, and military operations (Barnes and Evans, 2010; Jones and Schmidlin, 2011; Murphy and Burke, 2010). In the U.S. military, there is a trend to implement robotic systems that can perform some of the functions on the battlefield currently conducted by Soldiers (e.g., casualty extraction, explosive detection and disposals, reconnaissance and surveillance, supply transportation, building clearing, and firefighting, etc.; Barnes and Evans, 2010; Greenemeier, 2010; Osborn, 2011; Purdy, 2008; Singer, 2010). The same trend is manifesting itself in the civilian sector with the advent of the Goggle driverless car, autonomous farm equipment, and unmanned commercial aircraft (Mosher, 2012).

The inexorable trend towards greater societal reliance on unmanned systems begs the question of control. Based on numerous real-world experiences in robotics operations during emergencies (e.g., World Trade Center, Hurricane Katrina, and Utah Mine disaster), Murphy and Burke (2010) suggest that, with current technology, a two humans to one robot is a minimum ratio because of the safety issues involved. The ratio increases depending on the complexity of the environment and the degree of automaton. A higher ratio of humans is particularly important for combat environments, where fratricide or civilian casualties are possible. The ratio is high because of the limited situation awareness (SA) that the operator has when viewing the world from a robot's portal— not because a robot cannot be automated to navigate in difficult terrain.

However, this high ratio will not be sustainable if large numbers of autonomous systems are deployed for civilian and military applications. This will require supervision of not only single systems but also larger scale systems while maintaining an economically feasible ratio of humans to autonomous systems (Chen et al., 2011; Cummings et al., 2010). Increases in the sophistication and degree of autonomy will be necessary but not sufficient to maintain large scale unmanned systems, due to the human performance issues associated with increased autonomy: tunnel vision, misuse and disuse of automated systems, complacency, and degraded SA (Chen et al., 2011; Lee, 2008; Parasuraman and Riley, 1997). More germane to our current discussion, increases in autonomy may not overcome the human's span of apprehension limits around 7 (±2) related to monitoring multiple systems at the same time (Lewis et al., 2010; Miller, 1956; Wang et al., 2009).

In recent years, there have been several research efforts on developing intelligent systems that can assist the human operators to manage multiple robots in military tasking environments (Chen and Barnes, 2012a; Fern and Shively, 2009; Miller and Parasuraman, 2007). The purpose of this report is to review the literature on intelligent systems and discuss their efficacy in relation to

- efficient human supervision of multiple robots.
- appropriate human trust in the automated systems.
- maintenance of human operator’s SA.
- individual differences in human-agent (H-A) interaction.
- retention of human decision authority.

In the first part of this report (Sections 2 and 3), we review a number of topics from flexible automation to autonomous agents (e.g., mixed-initiative H-A teams, cognitive architectures) and point out the advantages and disadvantages of the various approaches. In particular, we will address the advantages of mixed initiative models to leverage both human and agent decision strengths. To illustrate one such approach, we discuss briefly some of our own research for a specific hybrid approach (RoboLeader) and present some of our major findings. In the second part of this report (Sections 4-6), we discuss in detail two key human performance issues (trust and SA) related to H-A teaming for multi-robot control. After reviewing research findings on these two issues, we also present some promising user interface design solutions to address these issues. Also in the second part of the report, we discuss briefly some key individual differences factors (operator spatial ability, attentional control ability, and gaming experience) that may impact H-A teaming in the context of robotics control. At the end of the report (Section 7), we briefly summarize some design guidelines based on our own and reviewed research.

2. H-A Teaming

Before we delve into the discussion of all the issues related to H-A teaming, a few notes on the terminology seem to be in order. While there are numerous definitions of “agent” (including intelligent agent, software agent, etc.), it is commonly accepted that an agent should possess the following characteristics: autonomy, observation of the environment (through some forms of sensors), action upon an environment (through some forms of actuators), and direction of its activity towards achieving certain goals (Russell and Norvig, 2009). The complexity of these systems varies greatly and ranges from a simple “reflex agent” (e.g., a thermostat) to an agent that can learn and evolve. While robots, by definition are agents, agents do not necessarily have physical embodiment. In the context of our current discussion, we will use the term agent to refer to a broader class of intelligent systems (with or without physical embodiment) that are consistent with the definition given above. We will use the term robots when the physical embodiment component is important in the discussion.

2.1 Characteristics of H-A Teams

Human-agent teams assume a relationship that goes beyond a human controlling or supervising agents (Inagaki, 2008). Teams are more than intelligent entities working on a common problem. Teams coordinate (share knowledge and depend on each other's output) and collaborate (work together on common functions) (Bradshaw et al., 2011). They share a common knowledge framework but it is not necessary that all team members have the same information; it is efficient for some team members to have specialized knowledge as long as they coordinate with the rest of the team (Cooke et al., 2000). Coordination requires communication among team members as well as shared knowledge. Effective teams can communicate implicitly as well as explicitly. Implicit communication depends on individuals knowing their role and how it intersects with other team members' roles to obtain tasking objectives. It is important to note that too much explicit communication can degrade team effectiveness as much as too little communication (Cannon-Bowers et al., 1998; Nikolaidis and Shah, 2012; Steinberg, 2012). Thus a H-A teaming relationship assumes:

- common knowledge
- shared understanding of objectives
- two-way communication

There are a number of ways to communicate with an agent. For example, communication can be implemented with graphical displays that can be updated by both the human and the agent while keeping both parties informed of the current state of the tasking objectives (Chen and Barnes, 2012b). In order to make H-A interactions as natural as human-human interactions, research efforts have been focusing on ways to support natural language communications between humans and agents (Tellex et al., 2011). Effective natural language communications require not only disambiguating the syntax and semantics of the utterance but also its pragmatics relating to the tasking environment and the intention of the speaker (Jurafsky and Martin, 2009). The current status of human-robot communications typically entails humans giving the robot a direct command and the robot trying to understand the command in terms of its physical environment. Even with relatively constrained environments, agents can be confused by ambiguous commands that humans could decipher easily (Cassenti et al., in review; Tellex et al., 2011). The additions of gestures, gaze-facilitated language processing, and better training protocols are enhancing the ability of humans and robots to engage in more natural two-way communications, but natural language processing (NLP) is still relatively unsophisticated compared to human-to-human dialogue (Camak and Thomaz, 2012).

However, the most important obstacle to effective H-A teaming is not NLP limitations but rather a shared understanding of the implicit goals inherent in complex environments. Trying to enumerate all possible intent situations is not practical. For example, telling a robot to go to the back door of a building and check for improvised explosive devices (IEDs) require not only sophisticated navigation and surveillance capabilities but also intent inferencing. For human teams, it would require a deeper understanding of the supervisor's intent including checking for IEDs or anything suspicious while moving towards the objective. Developing intent inferencing software has a long history; early attempts used pilot actions such as button pushes to infer the pilot's objectives (Rouse et al., 1990). These attempts proved to be too brittle and to have limited utility for real-world situations (Banks, 2002). Recently, more sophisticated software using intent-driven behavioral modeling have had some success in predicting human behaviors and intentions; however the solutions are more generic than would be practical for a typical human–agent problem space (Santos et al., 2012). Thus in the foreseeable future, it does not seem likely that an agent can communicate with humans as peers in any but the most constrained environment. This is due to unique human characteristics (discussed below) as well as communication limitations. The human role as part of the team equation is explored in the next sections.

2.2 The Human Role—Strengths and Weaknesses of Human Reasoning

Successful agent technologies take advantage of the differences between human and agent strengths, as human reasoning has very different characteristics than algorithmic reasoning (Bradshaw et al., 2011). Human-agent teams seem to be particularly effective for open-ended missions in which not all events can be pre-programmed (e.g., most combat situations). Agents can perform specialized functions but authority resides with a human supervisor for safety and tactical reasons (Barnes and Evans, 2010; Woods et al., 2004). This section reviews some of the most relevant human strengths and weakness in the context of H-A interaction for supervisory control tasks.

2.2.1 Human Rational Process

Johnson-Laird (2010) points out that humans are rational but do not use formal logic in everyday decision making. They tend to structure problems by focusing on only some of the possible logical implications, permitting humans to rapidly but sometimes erroneously solve real-world problems. Kahneman (2003) argues that many human decision processes are examples of bounded rationality. These strategies lead to quick decisions that have their evolutionary pedigree in the ability of humans to recognize dangerous situations without extensive processing. Klein (2008) points out that human intuition is not an inexplicable process but rather it involves matching multiple memory traces with current cues that alert humans to possible incongruities in the environment. Experts, in particular, are able to pick up on cues that allow them to circumvent detailed analysis (Klein and Jarosz, 2011). A good example involves Klein's interviews with expert fire fighters. The experts reported that considering various options during a fire could be fatal because of the time constraints involved. Klein posits that the Recognition Primed Decisions (RPD) process is frequently involved in such situations. A good solution seems to "pop-up," allowing humans to rapidly discover a safe course of action. This is not a magical process; RPDs are based on experts being able to abstract years of experience to serve them in times of danger. Finally, humans are able to understand not only the literal objective of a stated mission but also its intent and even its larger implications. Thus, an experienced commander may seize an unoccupied hill because he or she realizes its greater tactical value compared to the original objective. The decision may also be influenced by strategic objectives such as reducing civilian casualties. There is no guarantee that these decisions will be correct, but such flexible decision-making permits humans to arrive at nuanced solutions not simply rule-based ones. Recently, the RPD framework has been applied to the development of intelligent agents that can collaborate with humans in time-stressed situations, and section 3.1 will review some of the efforts in this area (Fan et al., 2010).

2.2.2 The Aspects of Human Emotion

Until recently, human emotional responses were neglected in most studies of human cognitive processes because emotions were considered a detriment or irrelevant to problem solving. However, more recent research has pointed out its importance to effective decision making (Damasio, 2010; Lee and See, 2004; Ramachandran, 2011). Emotions sensitize humans to subtle cues in the environment, creating an awareness of possible dangerous indicators that would be difficult to recreate artificially. There is a direct loop between possibly dangerous external stimuli and the human brain's emotional centers (amygdala) allowing for rapid although relatively unanalyzed responses to the stimuli. This would explain a Soldier's heightened sensitivity to changes in the immediate environment before executive functions in the neo-cortex have fully evaluated the situation (Goleman, 1995). Damasio (2010) also points out emotional centers in the brain have numerous interconnections to the executive centers in the frontal lobe, suggesting the importance of human emotional process in more reasoned decision making. Humans are not passive processors; particularly when their emotions are engaged, they are motivated to acquire new skills and to develop new approaches to problem solving in response to environmental changes. Another important advantage to the relationship between human cognition and emotion is the ability to empathize with other humans—making other humans' intentions more transparent. Recently, researchers have discovered mirror cells that are fired in relation to actions of another human suggesting that humans have specialized neurons for predicting the intentions of other humans (Ramachandran, 2011). In summary, human emotional capabilities are important because they are intimately related to human executive functions, sensitize humans to dangers and to opportunities in their environment, and are important in assisting humans to understand the intent of other humans by their body language and other subconsciously processed cues (Ramachandran, 2011).

2.2.3 Heuristics and Biases

The other side of the coin is the tendency of humans to use heuristics to solve real-world problems, especially in a time-constrained environment. Heuristic approaches lead to biases, which, in turn, lead to predictable errors (Barnes et al., 2011; Kahneman, 2003). For example, the availability heuristic depends on the ease of imagining an instance of an event rather than an understanding of the statistical likelihood of an event occurring (Tversky and Kahneman, 1974).

Parasuraman and Manzey (2010) examined the role of the "automation" bias for decision support systems, particularly its implication for complacency errors. Both phenomena are most salient in multitasking environments, for support systems that are highly accurate, and in situations where the outcomes are consistent (Rovira et al., 2007). One counterargument is that there is no bias or error involved—the participants were simply sampling information from different tasks in an optimal fashion; they were not ignoring the automated task, rather they were under-sampling automation to reflect the relative payoffs of sampling strategies in a high taskload situation (Moray, 2003). Parasuraman and Manzey (2010) detailed a series of studies that indicated the dynamics of the automation bias (i.e., complacency effects) were due to attentional deficits rather than sampling strategies or decision biases as described in Tversky and Kahneman (1974). The data of Chen and her colleagues (Chen and Barnes, 2012a; Chen and Terrence, 2009) supported this hypothesis that automation bias is related to the human operator's attentional control abilities (see section 6 on Individual Differences). In Parasuraman and Manzey (2010), the tasks involved supervisory control of five space station subsystems and automated fault diagnostic systems that provided fault diagnosis and suggested remedial actions. The aid suggested erroneous actions in 20% of the trials but allowed the participants (engineering students) access to the correct diagnostic information. The sampling behavior was suboptimal, but the most striking result was the type of errors the participants committed. Even when participants accessed correct diagnostic information, they tended to follow the (erroneous) aid-suggested course of action. Some of the participants even misreported accessing information that supported the incorrect remedial action —replicating the "phantom memory" effects found in previous automation bias research (Bahner et al., 2008). In a recent study, Manzey et al., (2012), further demonstrated that the human complacency behaviors are closely linked to attention (i.e., insufficient attention and incomplete verification, and inattentive processing of contradictory information). This is a crucial point that will be elucidated further in the Trust section (see also Chen and Barnes, 2012a).

2.3 The Agent Role—Strengths and Weaknesses of Machine Processing

Human factors researchers have been studying the relationship between machine and human skill sets since shortly after World War II—humans are more effective at inductive processes, judgments, and flexibility, whereas machines are better at repetitive actions, computation, and rapidity (Fitts, 1951). Hoffman et al., (2002) argues that humans and intelligent agent systems work most effectively in concert, not separated into skill domains. Optimization methods and algorithmic solutions are relevant if informed by human context and situational understanding, whereas humans perform more efficiently if they are supported by computational and symbolic processing. In both instances, it is the interaction of the human and the intelligent system that is important, not the singular advantage of one or the other (Bradshaw et al., 2011). Kahneman and Klein (2009) discussed the relative merits of human decision making and mathematical approaches such as regression equations. Kahneman and Klein pointed to early studies that showed human experts were often outperformed by statistical models for making predictions (e.g., clinical judgments, college admissions, patient success, officer retentions, etc.) even when the experts shared the same data sources. Experts tended to be overly influenced by personality factors compared to objective data trends. Thus for situations that were fairly stable, algorithms based on reliable data sources often outperforms humans. However, Klein pointed out that these approaches were not useful for rapidly changing situations or anomalous events requiring immediate decisions based on accumulated experience. Machine solutions inevitably improve as computer technology improves. Big Blue, the IBM super computer, now outperforms the best chess experts, and machine approaches can be expected to improve in all areas where optimization approaches are feasible; limits that are constantly being redefined as research into these areas continues (Russell and Norvig, 2009). An example more relevant to human-robot interaction was provided by Cummings et al., (2010)—it took the human operators (who were all experts) several minutes to solve a simple path planning problem but it only took the intelligent agent seconds to perform the same task. Nevertheless, Woods et al., (2004) point out that final authority for agent–human decisions is a human prerogative, because only the human can be a stakeholder and only the human can be held responsible for the outcome.

3. Agents for Human-Robot Teaming

In artificial intelligence, an intelligent agent is typically defined as "an autonomous entity which observes and acts upon an environment and directs its activity towards achieving goals" (p. 34; Russell and Norvig, 2009). This definition covers a variety of possible uses for intelligent agents, from swarms with individual agents of limited intelligence that evince sophisticated behaviors holistically, to agents that respond to particular tasks in a manner that emulates human intelligence. The necessity for more powerful intelligent agents that can interact with human operators in increasingly sophisticated ways will require that current capabilities be augmented with techniques and technologies that facilitate effective H-A team interactions (Bradshaw et al., 2011; Green et al., 2008). This section will first briefly review cognitive architectures relevant to human-robot interaction (HRI), and then we will discuss several types of agents that have been used in HRI tasks, including the RoboLeader agent that was developed in our own laboratory. Table 1 presents a summary of the technologies discussed in this section as well as strengths and weaknesses of each approach.

Table 1. Intelligent systems for multi-robot control.

Intelligent Systems	Potential Strengths	Potential Weaknesses	Key References
Cognitive Architectures	Use of machine learning, neural nets, and natural language processing algorithms that are compatible with human knowledge structures.	Less efficiency due to complexity inherent in cognitive approaches.	Laird et al., 2011; Kelley, 2006; Kurup et al., 2011
Teaming Agents	Supporting optimal task-allocation planning and flexible plan-execution; allowing graceful plan-degradations; facilitating proactive information distribution.	Human-Agent team performance more sensitive to the changes of tasking complexities (i.e., degrading faster) than Human-Human teams.	Fan et al., 2010; Korsah et al., 2012
Hierarchical agent	Greater flexibility in adjusting to task complexity (dividing task complexity between senior agents and specialized agents).	Communications among agents; difficulty in dealing with truly novel situations (algorithms too cumbersome when dealing with complex hierarchies).	Hou et al., 2011; Strenzke et al., 2011
Adaptive Automation	Balance between reducing workload for manual control and reducing SA loss for automated tasks; reducing the task management load; particularly useful in emergency situations.	Harmful effects associated with sudden changes in task state (triggered inappropriately); usurping delegation authority from the human.	Parasuraman et al., 2009; Steinhauser, et al., 2009
Adjustable Automation	Human initiating adaptivity of the joint human-system task.	Increased workload associated with selecting appropriate autonomy levels, especially under emergency situations.	Miller and Parasuraman, 2007
Mixed-Initiative Automation	Collaborative decision making between a human and an intelligent system.	Communication mechanisms between the agents and the humans to express their intents; mixed-initiative system's ability to respond to developments in the tasking environment.	Chen and Barnes, 2012a; Hardin and Goodrich, 2007; Tecuci et al., 2007

3.1 Cognitive Architectures

Cognitive architecture such as Adaptive Control of Thought-Rational (ACT-R) and Symbolic Cognitive Architecture (SOAR) were developed to mimic human intelligence using top-level symbolic systems based on production systems (i.e., if-then rules) as well as sub-symbolic processes (Kelley, 2006; Laird et al., 2011). The number of cognitive architectures has increased greatly in the last 30 years principally by coupling cognitive approaches with other artificial intelligence approaches. For example, Kurup et al., (2011) combined perceptual algorithms used in robotics with ACT-R to predict pedestrian behavior in urban street scenes. Early versions of ACT-R only mimicked intelligence because the knowledge is instantiated by the programmer and is not learned through an interaction of the software with the real world. More recent approaches, such as Symbolic and Sub-symbolic Robotic Intelligence Control System (SS-RICS), are being developed to control small robots conducting simple tasks such as walking through a door and finding an object hidden in the room (Kelley, 2006; Avery et al., 2006). SS-RICS uses production systems and semantic networks for knowledge representations and various learning algorithms that allow the robot to generalize its training trials to new situations. There are disadvantages to the cognitive approach as well; for many tasking environments, more efficient algorithms are available without the complexity inherent in cognitive approaches. The advantage of cognitive approaches is that such approaches use machine learning, neural nets, and NLP algorithms that are compatible with human knowledge structures (Jurafsky and Martin, 2009; Liu and Singh, 2004; Vinokurov et al., 2011). Human-like knowledge structures combined with NLP capabilities are essential if agents are to develop a peer-to-peer relationship in open-ended environments (Ball et al., 2010). ACT-R and NLP software are the basis of a synthetic teammate research project to emulate a unmanned aerial vehicle (UAV) pilot with an intelligent agent that is capable of generating natural dialogue with human team mates as well conducting UAV flight functions (Ball et al., 2010). The agent is not autonomous in that mission planning and mission objectives are supplied by human operators. The agent is being designed not only to interact with humans but to be a part of a UAV crew during realistic simulations—suggesting the possibility of humans and agents forming peer-to-peer relationships in the future.

3.2 Teaming Agents

In recent years, researchers have designed agents that support team behaviors. Korsah et al., (2012), for example, presented a multi-robot control system, called xBots, that could support optimal task-allocation planning and flexible execution of the plans as well as allow graceful degradations of the plans should failures or unexpected events happen. One key difference between the xBots system and other market-based approaches is that it optimizes the plans based on temporal constraints in the tasking environments. In order to facilitate natural interaction between humans and robots/agents, dialog management systems such as TeamTalk (Rudnicky et al., 2010) have also been developed. The effectiveness of TeamTalk has been evaluated in a simulated environment that involved multiple robots for search and rescue tasks (Marge et al, 2009). Other experimenters found that the type of communication among agents and human teams was important (Harbers et al., 2012). For example, Harbers et al. found that communication with agent team members concerning world knowledge of the tasking environment was not as effective as communicating the human's intent.

Other H-A teaming research and development efforts, while not directly applied to multi-robot control domains, are potentially useful for developing intelligent agents that can function as teammates to the humans in multi-robot tasking contexts. For example, Fan et al., (2010) presented research on agents that can support the development of shared mental models (see also Nikolaidis and Shah, 2012). These researchers discussed the use of the Collaborative Agents for Simulating Teamwork (CAST) model based on the RPD framework (R-CAST), which enables agents and humans to anticipate potential information needs and proactively exchange information between team members. The R-CAST agent architecture is based on the theory of shared mental models in human teams, proactive information distribution, and RPD (Klein, 2008). In essence, the objective of the R-CAST agent is to facilitate the "collaborative-RPD" process between the human operator and the agent by reasoning and representing the "contextual needs of collaboration" in the following areas: decision process (establishing shared mental models between the human and the agent), recognition aspects (cues, goals, expectancy, and courses of action), and the inference mechanism. Fan et al., (2010) conducted a human-in-the-loop simulation experiment and demonstrated that the H-A teams outperformed the human-human (H-H) teams in complex military command-and-control decision-making tasks, regardless of the time pressure imposed on the teams. However, the H-A team performance was more sensitive to the changes of tasking complexities than the H-H teams (i.e., degraded faster when tasks were more complex) than the H-H teams. The results of the Fan et al., (2010) suggest that using collaboration models such as R-CAST to form H-A teams may lead to better performance, although the overall H-A team performance may be moderated by tasking complexities.

3.3 Hierarchical Agents

In complex tasking environments, individual agents usually lack flexibility and thus may be able to perform only very circumscribed problem sets. For more complex problems, hierarchical agent systems are being designed with agents that have specialized intelligence embedded within multi-layer architectures. The individual agents have specific tasks and a means of communicating with other agents. The ability to divide task complexity between senior (more capable) agents and specialized (less capable) ones allows hierarchies to adjust to greater complexity and better adjust to change. The disadvantages are that as hierarchies become more complex, the algorithms to control them also become more cumbersome, and even then, agent hierarchies are still challenged by truly novel situations. Furthermore, the more levels involved and the more entities that need to be controlled, the more likely it is that communications among agents will become a serious problem.

Agent technologies with military import have been demonstrated for a number of realistic applications. For example, agents have been successfully used to control multiple UAVs with received signal indicator sensors to locate targets cooperatively during high fidelity simulations (Scerri et al., 2008). Researchers for the Defence Research & Development Canada demonstrated the utility of agent hierarchy technology (Adaptive Intelligent Agent [AIA]) for UAV control in a more complex simulation environment. Hou and his colleagues (Hou et al., 2011) used senior agents directing working agents which, in turn, directed junior agents. Their simulation demonstrated agents in concert with the operator, planning multiple UAV missions, navigating UAVs to the target area, and upon arrival directing sensors to locate the targets. Similar agent technology (e.g., the Cognitive and Cooperative Assistant System [CCAS]), has been used for cooperative control of multiple UAVs using live UAV demonstrators (Strenzke, 2011).

3.4 Flexible Automation

Flexible automation refers to systems that are neither fully automated nor fully manual but that invoke various levels of automation depending on the operator's state, critical events in the environment, or algorithms related to specialized problem sets. The approaches differ in their workload requirements (amount of cognitive resources available for tasks) and allocation of decision authority (Goodrich, 2010). Flexible automaton is a useful set of concepts for eliciting agents while minimizing workload depending on the requirements of the specific tasks in which agents are being used. The difference between the types of flexible automation involves the role of the human in decision making: (1) adaptive systems assign tasks under specified conditions decided on before the mission, (2) adjustable (also known as adaptable) automation requires humans to decide when to invoke automation during the mission, whereas (3) mixed initiative systems entail joint decision making (e.g., the planning process) throughout the mission (Parasuraman, 2007; Miller and Parasuraman, 2007; Tecuci et al., 2007).

3.4.1 Adaptive Automation

Adaptive systems are being developed to maintain a balance between reducing workload for manual control and reducing SA loss for automated tasks (Kaber et al., 2006). Adaptive automation is most effective for multitasking situations wherein a fully automated task may be neglected if the operator becomes complacent or allocates attentional resources to other tasks. A trigger based on environmental or internal state indicators is used to allocate tasks to either automation or manual control. During low workload, the task is allocated to the human and during high workload conditions the task is automated. The advantage compared to full automation is that it keeps the human engaged but not overwhelmed. Physiological measures (e.g., electroencephalography [EEG], functional magnetic resonance imaging, heart rate) have been used successfully in a number of laboratory settings as triggers to different workload states as well as to improve tracking performance (using switching rates of as low as 15s between automated and human control). It has also been used for adapting operator performance when controlling UAVs (Prinzel, 2000; Wilson and Russell, 2003). Operator error rates and task difficulty have been used as successful triggering mechanism to improve secondary tasks performance, to reduce mental workload and improve SA for supervisory control of UAV and unmanned ground vehicle (UGV) combined missions (Parasuraman et al., 2007). Because modern neurophysiological devices are becoming more cost effective and less invasive, future systems will most likely take advantage of this technology to monitor workload states (Barnes et al., 2006).

There are a number of technical and philosophical issues with adaptive systems (Miller and Parasuraman, 2007). If the trigger is less than perfect, then sudden changes in task state may be annoying or even dangerous. Furthermore, adaptive systems, by their very nature, usurp delegation authority from the human. On the other hand, it reduces the task management load; the operator does not have the additional task of deciding when or what tasks to automate (Goodrich, 2010). More importantly, when there are safety issues and time constraints such as a missile in-flight, the operator may not have the luxury of giving permission before the automated systems are activated (Barnes and Grossman, 1985). Parasuraman et al., (2009) and Steinhauser et al., (2009) provided several design guidelines for implementing adaptive automation based on their own experimental results as well as reviews of empirical research on adaptive automation and aiding (Chen et al., 2011).

3.4.2 Adjustable Automation

In adjustable (or adaptable) automated systems, in contrast to adaptive automation, the adaptivity of the joint human-system task is initiated by the human (as opposed to the automated systems in the case of adaptive automation (Goodrich, 2010; Langan-Fox et al., 2009; Miller and Parasuraman, 2007). The precise level of control is a matter of degree—we use a variation of the levels of autonomy (LOA) in Parasuraman et al., (2000), designating LOA-6 as the cut-off point for adjustable automation: the human operator must be given time and opportunity to veto an automation decision or make a decision on whether to automate. Thus, the machine can make decisions, but only the human can give permission to execute them. Miller and Parasuraman (2007) have developed an adjustable system they refer to as adaptable wherein specified algorithms known as *plays* can be elicited by the operator to improve performance during high workload mission segments. The plays can be instantiated either because they represent algorithms that can be handled better by machine intelligence or to reduce workload. The delegation model incorporated in their Playbook[*] regimen is specific to a task environment with a hierarchy of plays designed to obtain goals important to that environment. It has been used successfully for gaming situations such as RoboFlag, a capture the flag game using robots (Miller and Parasuraman, 2007). In a recent experiment, Miller et al., (2011) examined the effects of non-optimal Playbook solutions on operator performance. More germane to our discussion, the Playbook paradigm has also been used successfully to simulate UAV flights and has been used in simulation and field testing of UAV automation for the U.S. Army (Fern and Shively, 2009).

3.4.3 Mixed-Initiative Automation

Mixed initiative automation involves collaborative decision making between a human and an intelligent system much like the relationship between a human and a subordinate but autonomous assistant (Cummings et al., 2012; Tecuci et al., 2007). For example, the Mixed-initiative Activity Plan GENerator (MAPGEN) was developed by National Aeronautics and Space Administration (NASA) to aid planners for the Mars space mission (Bresina and Morris, 2007). MAPGEN used constraint reasoning to generate mission plans for the Mars mission based on priorities input by human planning experts considering science objectives as well as temporal and physical mission constraints. Initially, the constraints were considered “hard” parameters and the human could not override them even temporarily (although the final plan had to be approved by a technical committee). In subsequent software builds, MAPGEN constraints were relaxed, allowing human planners more flexibility in creating *what-if* scenarios, resulting in a more synergistic relationship between humans and MAPGEN. Another example examined the utility of a mixed-initiative system in the context of a simulated search-and-rescue task (Hardin and Goodrich, 2009). The study involved simulating 200 robots searching a large wilderness area for five lost hikers. For “adaptive” conditions, the decision determining the robots’ search

[*]Playbook is a trademark of Smart Information Flow Technologies.

pattern is triggered by discovery of cues relating to the hiker's location. In "adjustable" conditions, the human supervisor decides on the level of search responsibility for the robots. For the "mixed-initiative" condition, either the human or the robot can decide search responsibility when a cue is found depending on whom discovered the cue. In general, the mixed-initiative condition resulted in the best performance especially for the primary target detection task. Tecuci et al., (2007) point out that designing a mixed-initiative system requires consideration of seven issues: task parameters, control, shared awareness, communications, personalization, software architecture, and evaluation. This suggests that the system designers should not only consider the relative technical merits of the software agents and the human operators' capabilities but also the ability of both the agents and the humans to communicate their intents as well as the mixed-initiative system's ability to respond to developments in the tasking environment.

3.4.4 Combining Architectures

In reading the different descriptions of flexible automation, it is obvious that the different varieties are often blurred. In practice, adaptive systems can also be adjustable or even mixed. The rotorcraft's Pilot Associate program allowed a pilot to set parameters before the mission that determined under what conditions an adaptive process would be invoked (Parasuraman et al., 2007). Barnes and Grossman (1985) gave an example of a situation that was time sensitive. If a missile was noted by a pilot within a short time window (a few seconds), then the pilot could take evasive action; however, when the time window expired, the automated systems performed the maneuver without waiting for the pilot's permission. This was because the maneuver was useless when the deadline expired; the missile would inevitably destroy the plane if the pilot had failed to act. The point is that the different types of automation under investigation can be combined into complex architectures to deal with the real-world complexity. More complicated architecture such as the one suggested by Hou et al., (2011; discussed in section 3.3) that combine different types of flexible automation with various levels of intelligent agents are more likely to be used by designers of real-world systems. Real-world systems must conduct many types of missions under volatile conditions and be able to react to unforeseen circumstances rapidly. The latter constraint is an argument for the importance of H-A teaming within a mixed-initiative paradigm. Humans having final decision authority, however, does not imply that humans cannot delegate the authority to agents under specified conditions (Parasuraman et al., 2007).

3.5 RoboLeader

Past research indicates that autonomous cooperation between robots can improve the performance of the human operators (Lewis et al., 2010) as well as enhance the overall human-robot team performance (Schurr, 2007). Researchers have proposed a number of solutions to the potential issues of a robotic battlefield, such as setting up a robot call center in which robots query the human operator only when there is a problem (Xu et at., 2012). The operator makes the necessary adjustments but is not required to monitor robots continuously. A potential issue with this solution is that it requires the robots to be capable of self-diagnosing their own problems with high accuracy; additionally, the number of operator-robot interactions is expected to increase exponentially during the heat of combat, making the call center ineffective during the most critical time periods. Goodrich (2010) concluded that as the number of robots increases, there will be a maximum number that the human can monitor or control directly depending on the complexity of the environment or the state of the operator. Wang and his colleagues (Wang et al., 2009) reviewed a number of studies on supervisory control of multiple ground robots for target detection tasks and concluded that in order to be effective, "the Fan-out plateau lies somewhere between 4 and 9+ robots depending on the level of robot autonomy and environmental demands" (p. 143), limits very close to the classical (7 ± 2) findings for span of apprehension (Miller, 1956). Obviously, the human operator's attention issue is even more problematical when the operator must multitask as well as control the robot (Barnes and Evans, 2010; Chen and Barnes, 2012a; Chen et al., 2011; Chen and Terrence, 2008). Nevertheless, simply increasing the robots' level of autonomy does not resolve the issue. Since human operators' decision making may be influenced by "implicit goals" that the robots are not aware of (i.e., are not programmed into the behaviors of the robots; Linegang et al., 2006), human operators' involvement in mixed-initiative teams will still be required for the foreseeable future, especially in situations involving critical decision making. In other words, the human must always be in ultimate control for safety as well as flexibility reasons.

In order to evaluate some of the issues associated with intelligent agents for multi-robot control, the U.S. Army developed RoboLeader, an agent that can help the human operator coordinate a team of robots, as a research paradigm (Chen and Barnes, 2012a). Instead of directly managing each individual robot, the human operator only deals with one single entity—RoboLeader. The operator can, therefore, better focus on other tasks requiring his/her attention. More specifically, RoboLeader can collect information from subordinate robots with limited autonomy (e.g., collision avoidance and self-guidance to reach target locations), making tactical decisions and coordinating the robots by issuing commands, waypoints, or motion trajectories (Snyder et al., 2010). In typical mission situations, RoboLeader would recommend route revisions when encountering environmental events that require robots to be rerouted. The human operators, in turn, can accept the plan revisions or modify them as appropriate. RoboLeader, therefore, is a mixed-initiative system that consists of both human and machine decision-making components. It also possesses characteristics of hierarchical systems as RoboLeader serves as the interface between the human supervisor and the less capable (in terms of decision authority) robots.

A series of human-in-the-loop simulation experiments have been conducted to investigate the control structure and interface requirements between the human supervisor and RoboLeader, with number of robots, task-load, target mobility, agent error type, and agent reliability level being manipulated systematically (Chen and Barnes, 2012a; Chen and Barnes, 2012b). The first experiment established the feasibility of using RoboLeader to control up to eight robots during a reconnaissance mission (Chen and Barnes, 2012a). The results indicated equivalent target detection between RoboLeader and baseline conditions while reducing mission times by 12% for the RoboLeader condition. The second experiment focused on RoboLeader's reliability level (60% versus 90%) and type of possible errors (false alarm-prone [FAP] versus miss-prone [MP]; Chen and Barnes, 2012a). Results showed that the type of RoboLeader unreliability (FAP versus MP) affected operator's performance of visual scanning tasks (target detection, route editing, and SA). Overall, MP RoboLeader was more detrimental than FAP RoboLeader, although, paradoxically, participants showed better SA of the tasking environment due to constant scanning of the environment. The final experiment demonstrated the efficacy of RoboLeader in aiding the operator to conduct more dynamic missions, which required four robots to entrap a moving target (Chen and Barnes, 2012b). Results showed that the participants' target encapsulation task benefited from RoboLeader during all LOA conditions compared with manual performance, and that the intermediate LOA is sufficiently beneficial. Participants successfully encapsulated the moving targets only 63% of the time in the manual condition but 89% of the time when they were assisted by RoboLeader. Additionally, participants reported significantly higher workload when they were in the manual condition than when they were assisted by RoboLeader. Across all three experiments, participants with higher spatial ability consistently outperformed those with lower spatial ability in tasks that required the most visual scanning, regardless of the availability of RoboLeader and other experimental manipulations. Participants with higher attention control ability and those who played video games frequently were able to multitask better than their counterparts. Frequent gamers also repeatedly exhibited better SA of the mission environments than did infrequent gamers. Further discussion on these individual differences issues will be presented in section 6.

In general, the RoboLeader research suggests a synergy between humans and intelligent agents but not an equivalency. The agents were ideal for circumscribed solutions and as means to reduce the operator's burden of multitasking. However, it is essential to maintain the human's ultimate decision authority without affecting their awareness of the unfolding combat situation. The following section will review some of the key human performance issues in H-A teaming as well as potential user interface design solutions to mitigate those issues.

4. Human Performance Issues in H-A Teaming: Trust in Automation

In mixed-initiative operations, the human operator's trust in the automated systems is a critical element of the H-A team performance. There have been numerous definitions of trust in the literature of organization psychology, interpersonal relationship, human-machine interactions, just to name a few (Lee and See, 2004; Madhavan and Wiegmann, 2007; Mayer et al., 1995; Rempel et al., 1985). In the context of H-A interaction, Lee and See's definition of trust seems most relevant: "the attitude that an agent will help achieve an individual's goals in a situation characterized by uncertainty and vulnerability" (p. 54). According to Mayer et al., (1995) trust model (in the context of organization psychology), there are four major antecedents that contribute to trust development: the trustor's propensity to trust and the trustee's ability, benevolence, and integrity. Lee and See (2004), on the other hand, use the terms "performance, purpose, and process" to describe the aspects of "ability, benevolence, and integrity" for the discussion of trust developments in the context of human-automation interaction. It should be pointed out that over trust is as deleterious as under trust. Our assumption is that appropriate trust implies that humans understand an agent's limits as well as its benefits. The following sections review the system and environment-related factors as well as human-related factors in H-A trust. Potential system-design principles derived from research findings are also reviewed.

4.1 System and Environment-Related Factors

Lee and See's (2004) identification of antecedents for trust development in the context of human-automation interaction (i.e., purpose, process, and performance (3P's) provides a framework for discussion of system and environment-related factors that contribute to trust development. The "purpose" factor deals with the degree to which the automation is being used according to the designer's intent. The "process" factor deals with the question whether the algorithm of the automated system is appropriate for a given tasking situation. The "performance" factor deals with system reliability, predictability, and capability. A number of studies have examined the differences in people's perceived reliability of human versus automated aids (Dzindolet et al., 2001; Madhavan and Wiegmann, 2007). Although several factors may affect the perception (e.g., the context of the decision-making tasks, the operators' self-confidence in performing the tasks, the operators' monitoring strategies and expectations of performance of the systems, etc.), it was found that people tend to perceive the automation as being more capable and reliable than the human aids (when in fact the same info was provided to them). However, the caveat is that people are more sensitive to the automation's errors compared with another human's errors; this relative sensitivity leads to a more rapid drop in trust in the automated aids once errors are detected. Jian et al., (2000) also found that people are more willing to use stronger terms to describe their distrust in a machine versus a human.

Finally, Lyons and Stokes (2012) investigated the effects of risk on human operators' reliance on decision aids coming from another human verses an automated system. They found that, as the risk became greater, the human operators tended to rely more on the automation rather than the human aid. In a previous study conducted by the same group of researchers dealing with similar tasking environments (computer-based convoy scenarios involving an automated decision aid), it was reported that suspicion concerning the information technology (e.g., abnormal activities/behaviors, integrity of the data, validity of the output, access to the data, etc.) had different effects on human operators' self-assessed decision confidence than did the operators' trust and distrust in the automation (Lyons et al., 2011).

The issues related to trust in autonomous systems span multiple levels and encompass the social and ethical aspects. It is an ongoing debate in the HRI community regarding the locus of responsibility (human versus robot) when a robot commits a harmful act under a human's command, Kahn et al., (2012) showed that a robot may be perceived as unethical when it causes harms. Safeguard measures have been proposed to prevent robots from committing unethical or dangerous acts (Arkin and Ulam, 2012). Finally, as intelligent systems become increasing sophisticated and are capable to learn/evolve either based on their learning algorithms or access to information from other networks (e.g., cloud-based systems), it is imperative to examine the implications of these capabilities on operator trust in the systems. Since predictability is a critical aspect of trust development and maintenance, any learning behaviors may prevent the operators from properly calibrating appropriate trust. Section 4.3 will further discuss some of the system design strategies to mitigate these issues.

4.2 H-R Factors

When humans perceive automated systems as team members, their attitudes of misuse or disuse should develop as operators become familiar with the system, implying that the 'trust' decision is dependent on the attitude of humans towards automated systems. A distinction important to disuse or misuse of automation is the difference between *evaluation* errors and *intent* errors. For evaluation errors, the operator misperceives the optimal solution and commits a calibration error. For intent errors, the operator is aware of the aids superiority but still chooses to "disuse" automation in order to maintain control over the decision environment. For example, intent errors occurred when participants were aware of the superiority of an automated target detection aid but 84% of them still tended to disuse the aid, leading to suboptimal targeting decisions (Beck et al., 2007). This "disuse" error can be partially contributed to the operator's self-confidence in manually performing the task. Research showed that self-confidence is a critical factor in moderating the effect of trust (in automation) on reliance (on the automatic system) (Chen and Terrence, 2009; deVries et al., 2003; Lee and Moray, 1994). Lee and Moray found that when self-confidence exceeded trust, operators tended to use manual control. When trust exceeded self-confidence, automation was used more. Chen and Terrence showed that there is a strong interaction between the type of automation unreliability and participants' self-assessed attentional control, which will be discussed in the Individual Differences section (6.1).

Researchers suggest that the psychological context of the decision determines the tendency of the operator to disuse (under rely) or misuse (over rely on) automated systems (Parasuraman and Riley, 1997). In a series of experiments, Dzindolet et al., (2001) showed that by a simple change in decision order, "disuse" of an automated target recognition device changed to "misuse". If participants made a decision before being informed of the automated solution, they tended to rely on their own decisions even when they were suboptimal; whereas, in a related experiment using a similar paradigm, participants tended to over rely on the device whenever the automated solution was presented "at the same time" as the target scene. One explanation is that participants were attempting to reduce their cognitive load to maintain reasonable timeliness. However, such a strategy was not useful in the first experiment (automated solutions being shown after the participants made their decisions) because considering an alternative would increase workload by requiring operators to reconsider their original decisions. The workload hypothesis is supported by complacency research that indicates operators misuse automation in a multitasking environment but not in single task environment (Parasuraman et al., 1993). It has also been reported that both the cost of automation errors and the cost of verification affect humans' reliance on decision aids, and the effects are also moderated by age (Ezer et al., 2008). Generally, reliance is reduced as the cost of error increases and it is increased as the cost of verification decreases. However, younger adults are more flexible than older adults in changing their reliance behavior based on the changing cost structure. Since the older participants in the Ezer et al., (2008) study were over 65 years old, it remains to be seen whether a similar age effect can be observed for younger individuals.

Human operators' attitudes toward and trust in automated systems can also be influenced by their personalities (introversion versus extroversion; Merritt and Ilgen, 2008) and affective factors (e.g., moods and emotions; Merritt, 2011). Generally, Merritt and Ilgen found that extroverts tend to demonstrate a stronger propensity to trust the automation than do introverts but their trust also decline more readily if the system fails to behave as they expect. Merritt (2011) found that moods (e.g., happiness) significantly impacted the human operators' trust in an X-ray screening decision aid system, which was a better predictor of the operators' actual reliance on the system than was the operators' perceived accuracy of the system.

Recently, researchers have suggested that the trust in automation research addressed above is a foundation for modeling trust in human-robot interactions (Desai et al., 2009). Desai et al. suggest that the model account for the differences between current systems and those used in prior research; for example, the newer systems' levels of reliability and the more dynamic nature of the systems in terms of adjustable autonomy and their ability to carry out multiple tasks. There have also been efforts on developing training tools for reducing operator errors associated with disuse or misuse. For example, Beck et al., (2007) suggest that a combination of performance feedback and scenario training can reduce both appraisal and intent errors.

4.3 Implications for System Design—Trust Calibration

Lessons learned from a U.S. Naval Intelligent Autonomy program indicated that human operators sometimes questioned the accuracy and effectiveness of the output produced by intelligent systems such as those generating automated plans (Linegang et al., 2006). For example, some human operators indicated that they had difficulties understanding the rationales for some plans and how the plans were generated (Billman et al., 2005, as cited in Linegang et al., 2006). Additionally, some operators reported that they had difficulties at times when trying to specify mission parameters (e.g., goals and constraints) in the way required by the automated planning system (Billman et al., 2005). Furthermore, real-time development on the battlefield may require the human operator to change the plan for the robot team and/or for the individual robots. Lee and See (2004) recommended that the capabilities and limitations of the automated systems be conveyed to the operator, when feasible, in order for the operator to develop appropriate trust and reliance. For example, McGuirl and Sarter (2006) found that pilots' trust in an automated decision aid system was better calibrated when dynamic system confidence information was provided to them. Similarly, Seong and Bisantz (2008) reported that participants performed a target identification task significantly better and their trust better calibrated if provided with "meta-information" that informed them about the performance of the decision aid than those participants without the information. Bagheri and Jamieson (2004) demonstrated that when operators were aware of the context-related nature of automation reliability, their detection rate of automation failures increased significantly without affecting their concurrent tracking and system management tasks. The authors attributed this improvement in performance to a more effective attentional allocation strategy. Based on their findings on the different types of unreliable automation, Rovira et al., (2007) suggested that decrements in decision-making performance may be mitigated if operators can query the automation, inspect raw information sources, and verify or negate the automated advice. This remedy can potentially mitigate the "merging trust" phenomenon described in Keller and Rice (2010) where operator's trust in higher-reliability system was "pulled-down" by lower-reliability system (i.e., system-wide trust calibration versus. component-specific calibration). Roth et al., (2004) also reported that, in order to enhance the mixed-initiative team performance, the automated system should communicate to the human operator about its rationale for the system-generated plans while allowing the operator flexibility in comparing different alternatives and testing "what-if" scenarios. While excessive alerts may create the cry-wolf effect, Lees and Lee (2007) did find that "unnecessary alarms" (i.e., alerts that are legitimate but, due to the peculiarities of the situation, do not require operator compliance) foster the operators' trust in the automated system and actually enhance their compliance with the alerts rather than reducing it. Lees and Lee's data suggest that the three dimensions of trust (utility, predictability, and intent) need to be considered beside the traditional description of alarms according to signal detection theory (e.g., false alarm-prone or miss-prone).

Seppelt and Lee (2007) designed a display, based on the ecological interface design principles, which graphically portrayed the capabilities and limitations of a vehicle's adaptive cruise control for driving in various traffic and weather conditions. They found that drivers' reliance on the automation (i.e., cruise control) was more appropriate when the display was present than when it was not. In another study conducted by Lee's group on supervisory control of multiple robots with the assistance of an intelligent agent, it was reported that display transparency (overlays that portray robot status, target-related info, communications aspects, etc) not only enhanced the overall H-A team performance but also enabled better operator calibration of appropriate trust (reliance and compliance) in the agent. Lee (2012) proposed that, in order to increase automation transparency to the operator, system designers should make the 3P's as well as the history of the 3P's visible to the operator. However, the presentation should be in a simplified form, so the operator is not overwhelmed by the amount of information to process. Neyedli et al., (2011) showed that integrated displays that portray system reliability info and other task-related info (compared with separate displays showing the same info) were more effective in supporting appropriate automation-reliance behaviors in their simulated target identification tasks. Cook and Smallman (2008) also demonstrated the effectiveness of an integrated graphical display that promoted more comprehensive consideration of task-related info (i.e., less confirmation bias). Lee and See (2004) recommend that the automated system should propose a family of potential solutions, rather than just the optimal one. The user interface should also enable flexible adjustments of weighting of constraints via a user-friendly mechanism (e.g., sliders). Finally, Lee and See suggest that operators should be trained to understand the system's "expected reliability, the mechanisms governing its behavior, and its intended use" (p. 74).

Cummings et al,. (2010) evaluated an intelligent path-planning agent that assisted the human operators with a simulated maritime navigation task. The user interface of the planner agent was designed based on the objectives of promoting automation transparency and conveying environmental uncertainties while providing the participants with flexibility in specifying constraints for the solutions. Cummings et al., (2010) reported that, while the participants found the planner agent highly usable in terms of capabilities and reliability, they only rated it as somewhat trustworthy. However, the authors suggest that, for mixed-initiative system such as their planner agent, this level of trust is actually appropriate (i.e., not over- or under-trust), given the risks involved in the tasking environments.

Finally, Madhavan and Wiegmann (2007), based on the research findings of Nass and Moon (2000) on humans' social responses to computers, suggested that techniques such as anthropomorphizing of automation may help individuals better calibrate their trust in the systems. Specifically, the "humane" responses/characteristics exhibited by automation may reduce users' biases toward machines and facilitate their application of reciprocal behaviors. However, Lee and See (2004) cautioned that any anthropomorphizing of the automation should be carefully evaluated to ensure appropriate trust.

5. Human Performance Issues in H-A Teaming: Operator's SA of the Tasking Environment

One of the most critical factors for achieving effective supervisory control of multiple robots is maintaining adequate SA of the overall tasking environment as well as individual robots. There are three levels of SA as defined by Endsley (1995):

1. Perception of data and environmental elements
2. Comprehension of the current situation
3. Projection of future states and events

Changes in the environment that may affect the plans for the robots need to be detected and the plans need to be modified in a timely fashion. Kaber et al., (2006) evaluated the effectiveness of adaptive automation (in the context of air traffic control) for supporting different stages of information processing (i.e., information acquisition, information analysis, decision making, and action implementation; Parasuraman et al., 2000). They reported that automating the information acquisition part of the task was most beneficial for supporting SA.

Frequently, changes in the environment may require the operator to modify his/her plans for the robots. According to the National Transportation Safety Board (1994, as cited in Muthard and Wickens, 2002), nearly two-thirds of aviation accidents caused by faulty human decision making can be attributed to pilots' failure to revise their flight plans. Muthard and Wickens (2002) evaluated the effects of automation on pilots' performance in plan monitoring and revision. They found that pilots only detected about 30% of the experimenter-induced changes, which should have resulted in flight plan revisions. Plan continuation errors were especially pronounced when there was an unreliable automation aid as compared with no aid present. Mumaw et al., (2001) showed an even more alarming inadequacy in monitoring performance. In their study, pilots only detected about 3% (1 of 32 total cases) of unexpected changes to the mode of an automation aid. Indeed, it has been well documented that operators are frequently unaware of mode changes when interacting with automation systems and, therefore, are confused about the systems' behaviors (Sarter and Woods, 1995). In fact, data show that even if changes in the environment are detected, operators may have difficulty interpreting the relevance of the changes and their effects on the existing plans (Endsley, 1995).

There was some evidence that frequent video gamers tended to have better SA than did infrequent gamers in dynamic replanning tasking environments involving H-A teaming for multi-robot control (Chen and Barnes, 2012a; Chen and Barnes, 2012b). Given findings reported in Green and Bavelier (2006) that frequent gamers tend to have better visual short-term memory, it is not surprising to find them exhibiting better SA of the tasking environments.

More discussion on the effects of gaming experience will be presented in the section on individual differences. The rest of this section will discuss the issues related to multitasking and task switching, both of which have significant impact on the operators' development and maintenance of SA, as well as potential user interface solutions to address the SA issues.

5.1 Multitasking and Task Switching

On the future battlefield, Soldiers will very likely be expected to perform other tasks concurrently while operating a robot (or multiple robots) (Chen and Barnes, 2012a). While updates of information are needed, recent studies have also shown that interrupting a primary task (i.e., supervisory control of robots) with an intermittent task (e.g., communication messages) can have a negative impact on SA (Cummings, 2004; Dorneich et al., 2012). For example, Cummings (2004) found that instant messages diverted participants' attention from their primary task (simulated supervisory control of Tomahawk missiles), thus reducing their SA when returning their focus to the primary task. Therefore, the challenge is to identify the means by which operators can most effectively maintain SA.

Researchers have studied how characteristics of the automation (e.g., reliability and autonomy) and the task (e.g., complexity) may affect performance on these concurrent tasks, and the supervisory task as a whole. Manzey et al., (2012), for example, investigated performance consequences of automated aids (for fault identification and management) that are occasionally unreliable in a simulated multitasking supervisory control task. The results showed that automation benefits both primary (fault diagnosis) and secondary task (response to communications) performance. However, a significant automation bias effect was observed. In the first experiment, about half of the participants followed a wrong diagnosis generated by the automated system (versus only about 7% of participants committed the same error manually); in the second experiment, about 20% of those participants who had not experienced automation unreliability made commission errors (versus about 5% of those who had experienced system unreliability). Furthermore, in both experiments, about half of those who followed the automation wrongly actually made an effort to verify the appropriateness of the diagnosis. The authors observed that the data seemed to suggest individual's differences in susceptibility to automation bias effects. Section 6.1 will discuss individual differences in attention control ability and their effects on human interaction with automation. Finally, the Manzey et al., (2012) study reported that, with the highest level of automation, participants showed degraded "return-to-manual" performance. The authors, therefore, recommended that medium levels of automation be used if manual skills need to be maintained.

Simultaneous control of multiple robots may require the operator to switch attention/control among the vehicles from time to time. Basic research on costs of task switching consistently shows that people's responses tend to be substantially slower and more error-prone after task switching (Monsell, 2003; Rubinstein et al., 2001). There is some evidence that this cost may be reduced if the participants have a chance to prepare for the switch or receive task switching cues

(Monsell, 2003; Rubinstein et al., 2001). In the context of HRI, research has been conducted to investigate the effects of task switching on SA and operator performance (Crandall et al., 2005; Parasuraman et al., 2009; Squire et al., 2006; Wang and Lewis, 2007). SA may also be affected perceptually as a result of the change blindness phenomenon, which is the inability to perceptually attend to a change in one's environment. Parasuraman et al., (2009) examined change blindness in the context of a supervisory control task, in which participants were asked to monitor a UAV and a UGV video feed in a reconnaissance tasking environment. Parasuraman et al., (2009) found that change blindness occurred most frequently when a "distracter" was present, but also occurred while participants shifted their attention from the UAV monitoring task to the UGV monitoring task. These results also suggest that task switching during a robot supervisory task may incur change blindness, which by its very nature affects an operator's SA (additional information on task switching is provided in the next paragraph). According to Norman's (1986) seven stages of user activity, interruptions incur the greatest cognitive costs during the planning phases (intention forming and action planning) as well as the evaluation phases (outcome interpretation and assessment). Thus, interface designers should account for this, so that primary tasks are only interrupted during emergency situations or during moments of low workload (e.g., after evaluation is completed or before initiating a new plan). However, alerts should be provided to the operator indicating the changes to the interface and the degree of importance of the changes (Sarter et al., 2007).

5.2 Implications for System Design – Visualization and Attention Management

5.2.1 Visualization Tools

Proper uses of information visualization techniques can help the operators make sense of information and, thereby, enhance their SA of their tasking environments (for a review on human factors issues related to information visualization, see Robertson et al., 2009). Dong and Hayes (2012) showed that by presenting the operators simple bar graphs to indicate uncertainty aspects, the operators were able to distinguish ambiguous and unambiguous choices better than did those without access to the visualization display. This section highlights two most-researched visualization tools in the context of HRI and human-automation interaction, augmented reality and ecological interfaces.

Augmented Reality. Augmented reality (also known as synthetic vision) has been found to be an effective means to enhance pilot/UAV operator SA by portraying a more veridical view of the combat environment (Calhoun and Draper, 2006). For example, the U.S. Air Force has identified several candidate synthetic vision overlay concepts for UAV applications (Calhoun and Draper, 2006). The following information, potentially, can be overlaid graphically on the streaming video: maps and other synthetically generated symbology, photo-imagery, terrain elevation, laser range scans, past and potential future robot paths, updates via networked communication with other sources, cost functions related to plan optimization, and other vital statistical data (Cummings et al., 2012; Calhoun and Draper, 2006; Collett and MacDonald, 2006). However, large amounts of information, while helpful in reducing the operator's scanning effort by providing more data in a centralized area (e.g., the video), can create visual clutter and degrade operator's information processing (Wickens, 2005); on the other hand, Iani and Wickens (2007) suggested that the attentional tunneling effect of the augmented reality displays may not be as pronounced as previously suggested. Nevertheless, it is beneficial that a declutter capability be provided so the operator can customize the overlaid information presentation according to the situation and tasks (Calhoun et al., 2005).

Ecological Interface Designs. Ecological interface design (EID) is a user interface design technique that conveys the constraints in the tasking environment, usually visually via emergent patterns, so the operator can intuitively perceive and solve the problem (Vincente, 2002; Vincente and Rasmussen, 1992). Cummings and Bruni (2010) designed a user interface that supports a single operator's ability to control four UAVs simultaneously. They utilized a configural display (which conveys system-level information by portraying emergent visual features) to help the operator visualize the overall quality of plan revisions. In another study, Furukawa and Parasuraman (2003) demonstrated that EID was beneficial for enhancing human operators' detection of automation errors as well as their comprehension of system states. In their first experiment, Furukawa and Parasuraman (2003) showed that human operators, using an EID display showing an emergent perceptual feature, were able to detect significantly more system errors than when they used a non-integrated display (i.e., they showed significantly less automation-induced complacency). More strikingly, the operators were able to achieve better performance even though their visual attention to the EID display was significantly less, according to an eye movement analysis, indicating that their monitoring was more efficient. In the second experiment, Furukawa and Parasuraman showed the effectiveness of an EID display that portrays graphically the intention of the automated system. Their results showed that this visualization tool helped the human operators to achieve a better mental model of the system, which enabled them to make better decisions. In yet another study, Furukawa et al., (2004) integrated the intention-represented EID display in a partially-automated process control simulation and compared its effectiveness with that of an EID display without intention indicators of the automated system. Results showed that the intention-represented EID display was able to enhance the operators' predictions of the actions and behaviors of the automated system and, therefore, was able to improve the operator's action planning and decision making. Additionally, the benefits were demonstrated in novel scenarios, suggesting that the operators had a better mental model of the automated system with the intention-represented EID display than with the EID display without the intention indicators.

5.2.2 Attention Management Tools and Interruption Recovery Aids

When controlling multiple robots at the same time, it is inevitable that the operator will focus on some aspects of the environment (e.g., one of the robots) before resuming his/her monitoring of all the robots. Techniques that facilitate task resumption have been proposed and tested in various tasking environments (Ratwani et al., 2007; Scott et al., 2006; St. John et al., 2005). Some techniques focus on reminding the operator where they were before the interruption (Ratwani et al., 2007), while others present aids for the operator to quickly review what happened during the interruption (Scott et al., 2006; St. John et al., 2005). Ratwani and Trafton (2010) recommended that in interruption-prone tasking environments, care should be taken to ensure the operator's visual access to the primary task in order to facilitate task resumption after the interruptions. Ratwani et al., (2007) demonstrated that simply by reducing the size (by about 75%) of the window for the interrupting task (i.e., reducing the occlusion of the primary task screen by the interrupting task window), participants were able to resume their primary task significantly faster. Eye tracking data also showed that participants were more accurate at returning to where they left off. Other more sophisticated techniques to facilitate recovery from interruptions have also been developed. For example, St. John et al., (2005) discussed the utility of a SA recovery tool (named CHEX) which displayed a textual event history list in a naval air warfare environment (monitoring a geoplot of an airspace which contained ownship and approximately 50 other aircrafts). Other researchers have proposed replay tools that can communicate to the operators recent significant events via video. For example, Scott et al., (2006) presented two types of replay tools, one replaying the events at a 10× real time speed and the other presenting bookmarks on the event timelines so the operator could view the replay by selecting the bookmarks. Results showed that both replay techniques were effective, especially when the tasking environment was challenging. Based on the results, the authors presented several recommended design guidelines for interruption assistance interfaces:

1. Enable user control of event replay.
2. Provide visual summary of critical events but limit the summary only to goal-related events
3. Clearly indicate relationships between past and current system state (Scott et al., 2006; p. 703)

Dorneich et al., (2012) took a different approach and developed a wearable adaptive system, the Communications Scheduler, which used physiological sensors (EEG and electrocardiogram) to detect operators' cognitive workload in a multitasking situation (including navigation, cognitive, monitoring, and maintaining SA). The Communications Scheduler decided whether to interrupt the user's current task based on the urgency of the situation, the operator's cognitive workload, and the system state. The interruption etiquette was designed based on H-H interactions. Empirical testing showed that the Communication Scheduler positively impacted participants' performance by rescheduling their priorities, resulting in only a temporary loss of SA for low priority messages.

6. Individual Differences

Multi-robot control inherently involves multitasking. Multitasking environments often require the operator to switch their attention among the tasks effectively (e.g., receiving and processing intelligence data, sending spot-reports, maintaining communications with fellow crew members, etc.), with or without agents' help. Manzey et al., (2012) observed significant individual differences in susceptibility to automation bias effects in the multitasking environments they simulated, although the authors did not identify what individual differences factors contributed to the observed behaviors. Previous research has shown that some individuals show more performance decrements when multitasking than others and these decrements may be related to their poorer abilities to control and allocate attention (Feldman Barrett et al., 2004; Rubinstein et al., 2001; Schumacher et al., 2001). These results suggest that individual differences in attentional control seem to play a critical role in determining an operator's overall multitasking performance. Research also shows that individual differences in spatial ability and gaming experience play important roles in determining operators' SA in multi-robot tasking environments (Chen and Barnes, 2012a; Chen and Barnes, 2012b). The following section briefly reviews these individual differences factors that may impact the overall effectiveness of H-A teaming for multi-robot control.

6.1 Attentional Control

Attentional control is defined as one's ability to focus and shift attention in a flexible manner (Derryberry and Reed, 2002). According to a recent U.S. Air Force's survey of subject matter experts on the performance of UAV operators (Chapelle et al., 2010), attentional control is one of the most important abilities that affect an operator's performance since the robotics control task is inherently multitasking (e.g., sensor manipulation, tracking, communication, etc.). Past research has shown that poor attention allocation was related to degraded human performance in multi-robot control (Crandall and Cummings, 2007; Goodrich et al., 2005). Several studies have shown that there are individual differences in multitasking performance, and some people are less prone to performance degradation during multitasking conditions (Rubinstein et al., 2001; Schumacher et al., 2001). There is evidence that people with better attentional control can allocate their attention more flexibly and effectively, and attention-switching flexibility can predict performance of such diverse tasks as flight training and driving (Bleckley et al., 2003; Derryberry and Reed, 2002; Feldman Barrett et al., 2004; Kahneman et al., 1973).

Several studies showed that operators with lower attentional control interacted differently with automated systems than did those with higher attentional control; they tended to rely more heavily on automation, even when the reliability of those systems was low (Chen and Terrence, 2009; Chen and Barnes, 2012a; Thropp, 2006). For example, it appears that for high attentional control participants, false-alarm-prone systems tend to be more detrimental than miss-prone alerts, due to "disuse" of automation (although this difference is moderated by the ease of verification of the alerts' validity, as shown in Chen and Barnes, 2012a). For low attentional control participants, conversely, miss-prone automation was more harmful than false-alarm-prone automation, due to "misuse" of (i.e., over-reliance on) automation. According to Feldman Barrett et al., (2004), those with lower attentional control tend to take the "cognitive miser" approach (i.e., conserving the amount of cognitive resources) when dealing with complex information processing in order to reduce the attentional control requirements. When dealing with automated systems, therefore, it is likely that operators with different levels of attention switching abilities may react differently to unreliable automated systems. In other words, operators' behaviors of compliance with, and reliance on, automation may be moderated based on their ability to effectively switch their attention among the systems. For example, the well documented automation-induced complacency effects (Dzindolet et al., 2001; Parasuraman and Manzey, 2010; Thomas and Wickens, 2004; Young and Stanton, 2007) may be more severe for poor attentional control individuals compared with those with better attentional control. This phenomenon has been demonstrated in Chen and Terrence (2009) and Chen and Barnes (2012a).

Their results are consistent with past research that self-confidence is a critical factor in mediating the effect of trust on automation reliance (Lee and Moray, 1992; Lee and See, 2004). These findings have implications for designs of agents for multi-robot control. More research should also investigate training interventions (e.g., attention management) and/or user interface designs (e.g., multimodal cueing displays, automation transparency, and visualization techniques) that can mitigate performance shortfalls of those with lower attentional control (Chen et al., 2007; Chen et al., 2011; Dux et al., 2009).

6.2 Spatial Ability

Spatial ability has been found to be a significant factor in certain visual display domains (Stanney and Salvendy, 1995), multitasking involving flight asset monitoring and management (Morgan et al., 2011), virtual environment navigation (Chen et al., 2000), visual search task (Chen, 2010; Chen and Barnes, 2012a; Chen et al., 2008; Chen and Joyner, 2009; Chen and Terrence, 2008, 2009; Fincannon et al., 2012), and robotics task performance (Cassenti et al., 2009; Lathan and Tracey 2002). U.S. Air Force scientists (Chappelle et al., 2010; Chappelle et al., 2010) interviewed 53 subject matter experts about abilities that were critical to effective performance of UAV control tasks in terms of piloting and sensor operations—spatial ability was identified as an important factor for both tasks. Our previous research showed that individuals with higher spatial ability exhibited more effective visual scanning and target detection performance (Chen, 2010; Chen and Barnes, 2012a; Chen and Barnes, 2012b; Chen et al., 2008;

Chen and Joyner, 2009; Chen and Terrence, 2008, 2009). Based on these findings, it seems reasonable to expect operators with higher spatial ability to perform better with agents in multi-robot control tasking environments, especially if more spatial information processing is required from the human. Alternatively, training interventions that could enhance the spatial interpretations required to perform a mission task might also be of benefit (Baldwin and Reagan, 2009).

6.3 Gaming Experience

According to Green and Bavelier (2006) and Hubert-Wallander et al., (2010), experienced action video game players, compared with infrequent/non- gamers, were found to perform significantly better on tasks that required visuo-spatial selective attention, multiple object tracking, rapid processing of visual information and imagery, and flexibility in attention allocation. Hambrick et al., (2010) also demonstrated the relationship between video game experience and multitasking performance. A U.S. Air Force study (Triplett, 2008) concluded that, based on interviews of UAV pilots, gamers' superior visual information processing skills may be able to translate into superior robotics management performance. Indeed, a recent U.S. Air Force study (McKinley et al., 2010) found that frequent video gamers outperformed infrequent gamers on robotics (UAV) tasks and, in some cases, performed as well as experienced pilots. Additionally, Cummings et al., (2010) found that frequent gamers collaborated more with an automated UAV replanning system (higher degree of consent) than did infrequent gamers. Finally, Chen and Barnes (2012a) and Chen and Barnes (2012b) demonstrated that frequent gamers exhibited significantly better SA of the tasking environments than did infrequent gamers. Based on these findings, therefore, it is expected that frequent gamers may work better with agents in multi-robot control tasking environments due to their superiority in visual attention allocation and information processing.

7. Agent as Personal Assistants for Supervisory Control of Multiple Intelligent Systems

Most agent technologies that we reviewed have the same drawbacks; that is, they require focused attention, have high workload demands, and cause diffusion of SA when multiple agents are involved. The problem becomes more acute as the number of intelligent systems increases and the human operator is expected to multitask (Barnes and Evans, 2010; Chen and Barnes, 2012a). RoboLeader is closer to the concept of a *personal assistant agent* (e.g., the Cognitive Assistant that Learns and Organizes (CALO) project, see Yorke-Smith et al., 2012) rather than a specialized robotic entity (Barnes and Grossman, 1985; Jones and Schmidlin, 2011). The principle advantage of the personal assistant concept is that the agent interfaces directly with the operator in order to coordinate other intelligent systems—freeing the operator for other tasks such as for scanning other information sources. The agent is also an interface conveying information from the subordinate intelligent systems to the human operator and vice versa. The final version of an intelligent agent as a personal assistant needs to be refined and some of our preliminary assumptions need to be tested. Also, some of the guidelines are not currently feasible and depend on future research in such areas as machine learning, natural language, and cognitive architectures (Kelley, 2006). Based on the literature and RoboLeader research, the following are our initial "best guess" guidelines for an agent as a personal assistant in non-routine environments especially when safety is involved (e.g., combat):

a. **Agent/human interaction needs to be flexible**. The system should be able to adjust to operator workload and to allow agents to act autonomously under specified conditions (Goodrich, 2010; Tecuci et al., 2007).

b. **Operators must have ultimate decision authority,** The mechanism for ensuring human authority needs to be embedded in the agent architecture (e.g., mixed initiative systems); however, if human supervisors are "out of the loop" too long, complacency effects will occur (Endsley and Kiris, 1995; Fern and Shively, 2009; Parasuraman and Riley, 1997; Parasuraman and Manzey, 2010; Woods et al., 2004).

c. **Humans and agents have different cognitive characteristics**. Mathematical or algorithmic solutions for well defined problem spaces are best handled by agents; uncertain situations that are poorly defined or problems that have meta-consequences are best handled by experienced humans (Bradshaw et al., 2011; Kahneman and Klein, 2009).

d. **Automation transparency is essential**. Bi-directional communications between the operator and the agent need to be facilitated so the operator can understand the agent's intent and vice-versa. Intent understanding and communication with agents is limited but is currently feasible for specific task environments. A personal agent's cognitive architecture should be designed to be congruent with human cognition (Avery et al., 2006; Chen and Barnes, 2012a; Jones and Schmidlin, 2011; Tellex et al, 2011).

e. **Human individual differences must be part of the human/agent design process**. This can be accomplished either by selection, training or even designing agents that are sensitive individual differences among humans (Chen and Barnes, 2012a; Chen and Barnes, 2012b).

8. Conclusions

We have reviewed a number of specialized examples of agent technology for multi-robot control and human performance issues that need to be taken into account when designing such systems. The proliferation of agent technology will likely keep progressing and be used increasingly in more complex environments—both because of improvements in computing power and the development of more sophisticated algorithms. Artificial agents are able to supplement human intelligence by their use of more formal logic and their use of complex optimization algorithms to solve circumscribed problem sets. Human cognitive strengths, in turn, can be complementary to artificial intelligence capabilities. In the context of military operations, agents can reduce Soldier workload by being able to attend to multiple functions that might overwhelm Soldiers during the heat of combat. However, no set of agents in the foreseeable future will be able to understand, for example, the nuanced political and ethical implications facing U.S. ground troops (Linegang et al., 2006). Therefore, for most situations, complete agent autonomy is not desirable, especially in the near or mid-term. Rather, H-A teams and mixed-initiative tasking have the greatest potentials of supporting fluid interactions between humans and agents while taking advantage of the strengths of both. Agents can be delegated to perform specific task autonomously but only with the permission of the human operator and, if possible, only if the human is able to intervene when necessary. For future H-A teams, a crucial link will be implicit and explicit communication between humans and agents. NLP by itself is insufficient; some ability to have a common cognitive understanding and for both the human and robot to communicate their intentions will be necessary (Chen et al., 2011). Also as pointed out by Lee (2008) in his review of the seminal article on human-automation interaction by Parasuraman and Riley (1997), "automation requires more, not less, attention to training, interface design, and interaction design" (Lee, 2008, p. 404). As suggested by Parasuraman and Manzey (2010), automation does not replace the human, rather, it changes the nature of the human's task.

The missing element in current research is the development of a true partnership between humans and artificially intelligent entities. Work cited suggests the underpinning of partnership relationship in trust, artificial animal surrogates, advanced interfaces, collaborative behaviors, supervisory control allocated to robotic entities, and even shared ethical values. Whereas these ongoing research investigations all contribute to the advancements in H-A teaming capabilities, one of the most important elements of true H-A partnership, shared linguistic awareness, is still in a nascent state (Tellex et al., 2011). Natural language interfaces by themselves are not sufficient for peer relationships which require more robust shared cognitive architectures that allow the artificial entity to infer intent, generalize instructions, and participate in a problem solving dialogue in novel situations. Intelligent agents in a mature state that can operate as partners in truly complex environments will most likely not be available in the short term. However, continuing research to understand the characteristics of partnership relationships is an important requisite for understanding the boundaries of the relationship (Chen and Barnes, 2012a; Chen and Barnes, 2012b). For example, delineating H-H problem solving in environments of interest will help to isolate cognitive factors necessary to communicate in novel environments. Investigating cognitive architectures in simpler environments will help measure what variables influence peer synergy for intent inferencing and two-way dialogues. There is no requirement for intellectual equality between human and artificial agents; the important issue is to understand what factors are necessary for partnership problem solving in truly complex real world environments.

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List of Symbols, Abbreviations, and Acronyms

3P’s	purpose, process, and performance
ACT-R	Adaptive Control of Thought-Rational
AIA	Adaptive Intelligent Agent
CAST	Collaborative Agents for Simulating Teamwork
CALO	Cognitive Assistant that Learns and Organizes
CCAS	Cognitive and Cooperative Assistant System
EEG	electroencephalography
EID	Ecological interface design
FAP	false alarm-prone
H-A	human-agent
H-H	human-human
HRI	human-robot interaction
IED	improvised explosive device
LOA	levels of autonomy
MAPGEN	Mixed-initiative Activity Plan GENerator
MP	miss-prone
NASA	National Aeronautics and Space Administration
NLP	natural language processing
R-CAST	Recognition-Primed Decision (RPD) framework
RPD	Recognition Primed Decision
SA	situation awareness
SOAR	Symbolic Cognitive Architecture

SS-RICS	Symbolic and Sub-symbolic Robotic Intelligence Control System
UAV	unmanned aerial vehicle
UGV	unmanned ground vehicle

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