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Supervisory Control of Unmanned Vehicles

by Jessie Y. C. Chen, Michael J. Barnes, and Michelle Harper-Sciarini

ARL-TR-5136 April 2010

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ARL-TR-5136 **April 2010**

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REPORT DOCUMENTATION PAGE

Form Approved
OMB No. 0704-0188

1. REPORT DATE *(DD-MM-YYYY)*	April 2010
2. REPORT TYPE	Final
3. DATES COVERED (From - To)	June 2008–June 2009
4. TITLE AND SUBTITLE	Supervisory Control of Unmanned Vehicles
5a. CONTRACT NUMBER	
5b. GRANT NUMBER	
5c. PROGRAM ELEMENT NUMBER	
5d. PROJECT NUMBER	622716H70
5e. TASK NUMBER	
5f. WORK UNIT NUMBER	
6. AUTHOR(S)	Jessie Y. C. Chen, Michael J. Barnes, and Michelle Harper-Sciarini*
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)	U.S. Army Research Laboratory ATTN: RDRL-HRM-AT Aberdeen Proving Ground, MD 21005-5425
8. PERFORMING ORGANIZATION REPORT NUMBER	ARL-TR-5136
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)	
10. SPONSOR/MONITOR'S ACRONYM(S)	
11. SPONSOR/MONITOR'S REPORT NUMBER(S)	
12. DISTRIBUTION/AVAILABILITY STATEMENT	Approved for public release; distribution is unlimited.
13. SUPPLEMENTARY NOTES	*Institute for Simulation and Training, University of Central Florida, 3280 Progress Dr., Orlando, FL 32826

14. ABSTRACT

The purpose of this report is to review research pertaining to the limitations and advantages of supervisory control for unmanned vehicle (UV) systems. We identify and discuss results showing technologies that mitigate observed problems, such as specialized interfaces and adaptive systems. In the report, we first present an overview of definitions and important terms of supervisory control and human-agent teaming. We then discuss human performance issues in supervisory control of UVs with regard to operator multitasking performance, trust in automation, situation awareness, and operator workload. In the following sections, we review research findings for specific areas of supervisory control of unmanned air vehicles, unmanned ground vehicles, and heterogeneous UVs (i.e., using different types of UVs in the same mission). In the last section, we review innovative techniques and technologies designed to enhance operator performance and reduce potential performance degradations identified in the literature.

15. SUBJECT TERMS

performance, user interface design, supervisory control, unmanned vehicle, robotics operator

16. SECURITY CLASSIFICATION OF: a. REPORT	b. ABSTRACT	c. THIS PAGE	17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON	19b. TELEPHONE NUMBER (*Include area code*)
Unclassified	Unclassified	Unclassified	UU	60	Jessie Y. C. Chen	407-384-5435

Standard Form 298 (Rev. 8/98)
Prescribed by ANSI Std. Z39.18

Contents

List of Figures

List of Tables

Acknowledgments

This report was sponsored by the Safe Operations of Unmanned Systems for Reconnaissance in Complex Environments Army Technology Objective of the U.S. Army. The authors wish to thank Mr. Bryan Clark for his assistance in preparing the manuscript. The authors also wish to thank the reviewers for their helpful comments.

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1. Introduction

Unmanned vehicles (UVs), including unmanned air vehicles (UAVs) and unmanned ground vehicles (UGVs), are becoming an essential part of the battlefield. The Armed Forces have large programs for developing robotic systems (Barnes, in press) that encompass aerial, sea, ground, and subterranean applications. Future warfare will depend on collaboration among UVs, not only within services but also between services, and eventually among allied partners. Battlefield collaborations will involve hundreds of UVs as well as an equal number of manned systems requiring novel techniques, such as call center approaches, to monitor the unfolding decision environment. The complexity and sheer number of mixed assets in future operations will require increased autonomy and problem-solving capabilities for unmanned systems (Lewis et al., 2006). Furthermore, to maximize human resources, it will be desirable to designate a single operator to supervise multiple UVs, adding to his or her already heavy task load (Barnes et al., 2006b; Chen et al., 2008). However, having systems with automated behaviors introduces its own set of problems, including overreliance on the automated systems, potential situation awareness (SA) degradations, and possible loss of skills to perform the tasks manually when automation fails (Klein et al., 2004; Parasuraman and Riley, 1997; Parasuraman et al., 2000).

The purpose of this report is to review research pertaining to the limitations and advantages of supervisory control for UV systems. More importantly, we identify and discuss results showing technologies that mitigate observed problems, such as specialized interfaces and adaptive systems. In the following section, we first present an overview of definitions and important terms of supervisory control and human-agent teaming. We then discuss human performance issues in supervisory control of UVs with regard to operator multitasking performance, trust in automation, SA, and operator workload. In sections 3–5, we review research findings for specific areas of supervisory control of UAVs, UGVs, and heterogeneous UVs (i.e., using different types of UVs in the same mission). Finally, in section 6, we review innovative techniques and technologies designed to enhance operator performance and reduce potential performance degradations identified in the literature.

1.1 Supervisory Control - Overview

Supervisory control of technology may be defined in terms of human information processing and the operator's role in a given task, or from the perspective of the level of automation employed and the types of operator interactions with the automated technology. Humans play a variety of roles in supervisory tasks, including planning, teaching, monitoring, intervening, and learning (Sheridan, 2002). These roles typically occur in the temporal order described and may repeat throughout a supervisory task. Sheridan (2002) describes these roles in sequence as (1) planning the course of action before the automation is activated, (2) instructing the computerized technology to perform a task in a particular manner, (3) monitoring the instructed automation to be sure it goes as planned, (4) intervening, when necessary, to adjust or correct the automation, and (5) learning from the performance and outcomes of the automation in order to improve planning for future interactions. As task complexity increases, there is greater need for planning and teaching. In addition, the need for monitoring and intervening depend on the quality of planning and instruction.

1.1.1 Level of Autonomy

When implementing a supervisory control task, the amount and types of human interaction with the automated technology must be considered in order to determine the appropriate level of automation to employ. Parasuraman et al. (2000) have defined human interaction with automated technology in terms of 10 "levels of automation of decision and action selection" that are based on four stages of human information processing: (1) information acquisition, (2) information analysis, (3) decision and action selection, and (4) action implementation. The 10 levels of automation are defined in table 1, which has been modified from the original table 1 appearing in Parasuraman et al. (2000). There are risks, benefits, and consequences associated with each level of automation in terms of the associated mental workload, reliance on the automation (which introduces the issues of trust and reliability of the automation), and the human operator's level of SA (see Parasuraman et al., 2000). Therefore, it is important to plan for a level of automation (LOA) that provides a balance of human workload that is challenging to the operator, yet manageable, and that also provides a level of SA sufficient to meet task performance goals. For example, automation level 10 excludes the human operator from making decisions and taking actions; thus, the supervisory *monitoring* role of the human becomes a vigilance task, which can lead to operator complacency, resulting in human performance errors.

Table 1. The 10 LOAs of decision and action selection (modified from table 1 in Parasuraman et al. [2000]).

High	**10**	Full autonomy: the computer makes all decisions, acts autonomously, and ignores the human operator.
	9	The computer informs the human operator, only if it "decides" to.
	8	The computer informs the human operator, only if asked to.
	7	The computer executes automatically, then informs the human operator as necessary.
	6	Allows the human a limited amount of time to veto an action before it is automatically executed.
	5	The computer executes the suggestion with approval from the human operator.
	4	The computer suggests one alternative.
	3	The computer narrows the decision making to a few selections.
	2	The computer offers a complete set of decision/action alternatives.
Low	**1**	Manual operation: the computer offers no assistance to the human operator, who must make all decisions and take all actions.

1.1.2 Human-Automation Interactions

Supervisory control may also be defined in terms of the coordinated interactions that occur between the human and the automation, referred to here as human-agent (H-A) teaming. Researchers have referred to H-A teaming as team play (Dekker and Woods, 2002; Klein et al., 2004; Sarter and Woods, 2000). These researchers argue that the interactions between the operator and the automation should be the focus of supervisory task designs. Researchers have empirically investigated how constructs associated with team play (e.g., common ground) may be facilitated by the characteristics of the automation during an exploration task. Stubbs et al. (2008), for example, studied how common ground could be facilitated among a (simulated) globally distributed team of operators and exploration robots. More specifically, Stubbs and her colleagues investigated how introducing a robot proxy would influence the degree of collaboration the operators perceived they were engaged in during the task. The robot proxy assisted the operator with planning and supervised the less autonomous robots. Results indicated that those who were assisted by the robot proxy reported higher perceptions of collaboration than those who did not use the robot proxy. Furthermore, those who used the robot proxy had improved performance and more accurate mental models of the robot team's capabilities, and were more efficient at the exploration task.

Concepts such as common ground and other human-team processes (e.g., coordination and communication) may provide a compressive understanding of H-A coordination (Fiore et al., 2008; Stubbs et al., 2008). H-A coordination is similar to human-team coordination in that they both address interdependency and dynamic interplay among team members. Given these similarities, the processes that occur during human-team coordination may very likely emerge during H-A coordination (Cuevas et al., 2007). For example, communication, a team process, emerges from the exchange of information between the operator (who may, for example, request information) and the automation (which may provide information about the state of the system and the operating environment). In sum, the team behaviors that occur during a supervisory task will illuminate relevant team processes. Knowing what team processes are necessary and understanding how they will affect the outcome of H-A coordination can inform the design of supervisory tasks.

The following section discusses in detail some of the major human performance issues associated with supervisory control of multiple UVs. Particularly, we discuss operator multitasking performance, trust in automation, SA (issues associated with tasking switching and error diagnosis and recovery), and operator workload.

2. Operator Performance Issues in Supervisory Control of UVs

2.1 Operator Multitasking Performance

In the future battlefield, Soldiers will very likely be expected to perform other tasks concurrently while operating a robot (or multiple robots) (Mitchell and Chen, 2006). In addition to the multitasking requirement, operators' overall performance may be affected by other factors, such as situation understanding, mental workload, trust in the automated systems with less than perfect reliability, and tasking environment and stress (e.g., time constraints and fatigue). For example, Manzey et al. (2008) 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 (i.e., fault diagnosis) and secondary task (i.e., response to communications) performance. However, a significant automation bias effect was observed. About half of the participants followed a wrong diagnosis generated by the automated system. Additionally, with the highest LOA, 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.

Recent multitasking studies have investigated combining navigation tasks concurrently with targeting and firing (search and destroy) tasks and intermittent communication tasks (Chen and Joyner, 2009; Cummings and Guerlain, 2007). Typical navigation task manipulations have included perception (egocentric vs. exocentric), attention (number of robots to control simultaneously), and communication with teammates. To increase task complexity, search and destroy tasks have manipulated attentional resources by increasing the number of targets or gunner stations to command. The multitasking study by Chen and Joyner (2009) required an operator to perform a gunner task, detecting and firing upon targets, while simultaneously either managing a semi-autonomous UGV or teleoperating or monitoring a UGV. A third intermittent task required participants to simulate communication with a gunner crew. Results showed that overloading the operator's mental capacity with multiple complex tasks simultaneously led to performance decrements; however, when (semi-) autonomy was given to robotic entities, the operator could focus cognitive resources on complex tasks while simply monitoring (rather than controlling) the semi-autonomous robots, intervening only when necessary.

Cummings and Guerlain (2007) tried to determine the approximate number of autonomous vehicles that one operator could efficiently command and control simultaneously, under a low- or high-tempo multitask condition. Their study involved commanding missile launches while being distracted by intermittent communication messages. Participants in this study demonstrated that 16 missiles were the limit to control before performance degradation was observed. Cummings and Guerlain cited that their findings corresponded with air traffic control (ATC) studies, where 17 managed aircraft were the limit that operators could handle well. Other studies have concluded that a fewer number of UAVs could be controlled simultaneously (Miller, 2004); however, it is important to consider the levels of automation applied to the autonomous entities. In many cases, the more manual operation that was demanded, the fewer entities that could effectively be supervised (Ruff et al., 2002).

Factors that impact supervisory control of decision-making tasks include degrees of coherence (comprehensiveness, consistency, and rational soundness) and correspondence (accuracy) of the information available for these tasks (Mosier et al., 2007). Since coherence is a prerequisite to correspondence, Mosier et al. (2007) studied the effects of coherence (i.e., information congruence) in the context of time pressure and operator confidence. In their study, airplane pilots were found to make quicker, less accurate decisions under time pressure, as they did not utilize all of the cues available to them. Instead, they tended to use cognitive heuristics such as anchoring the most salient cues to satisfice rather than take the time necessary to make a better-informed decision. Satisficing was also observed in the supervisory command and control study by Cummings and Guerlain (2007) in which participants, who were under a time constraint, had to select one of several missiles to redirect toward a target. Participants often redirected a missile that was suboptimal, yet sufficient, to complete the mission.

2.2 Trust in Automation

Trust in automation is probably misleading because trust has the connotation of a prescribed behavior. Calibration is a more fitting term because it suggests that operators intervene only when they have reason to believe their own decisions (od) are superior to the automated system's decisions (ad). In decision theoretic terms, operators choose to use automated systems when the probability of a correct decision (Pc) meets the following criterion (Dzindolet et al., 2001a):

$$\text{Intervene if } P(c)\ od > P(c)\ ad$$

However, operators have a difficult time assessing their own accuracy. In general, humans tend to be poorly calibrated, often overestimating their own abilities (Fischhoff et al., 1977). This implies that humans will overvalue their own decisions in comparison to automated solutions. However, the opposite tendency for humans to over-rely on automated systems has been shown by a number of researchers (Chen and Terrence, 2008, 2009; Dzindolet et al., 2000; Mosier and Skitka, 1996; Parasuraman et al., 1993; Thomas and Wickens, 2000; Young and Stanton, 2007). The psychological context of the decision determines the tendency of the operator to disuse (under-rely on) or misuse (over-rely on) automated systems (Parasuraman and Riley, 1997). In a series of experiments, Dzindolet et al. (2001b) 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 (Barnes et al., 2006a). The workload hypothesis is supported by compliancy research that indicates operators misuse automation in a multitasking environment but not in single-task environment (Parasuraman et al., 1993).

Another distinction important to "trust" decisions 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 aid's 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).

The reliability of the automated system also impacts operator calibration. A number of researchers reported that target cueing is ineffective below a certain level of reliability (~60%–70%) (Wickens and Dixon, 2005; Wickens et al., 2006). In their meta-analytic study, Wickens and Dixon found that "a reliability of 0.70 was the 'crossover point' below which unreliable automation was worse than no automation at all." Reliable automation enhances performance (Rovira et al., 2007); however, even reliable aids tend to be disused if the few mistakes the aid makes are obvious, such as failing to detect a target when it is plainly visible (Dzindolet et al., 2006). However, the converse, automation paradox, is also evident; operators tend to over-rely more on highly accurate aids when advisories are incorrect. That is, operators are more complacent when they develop trust in automation with high reliability because the possibility that the aid will mislead them is perceived as minimal (Parasuraman et al., 2007; Rovira et al., 2007).

The type of unreliability has an important impact on the operator's perception of and response to system alerts. Cueing systems for the automated systems are often false-alarm prone (FAP) or miss-prone (MP), based on the threshold settings of the alert. Wickens et al. (2005b) showed that the operator's automated task (i.e., system failure monitoring) performance degraded when the false alarm (FA) rate of the alerts for the automated task was high. In other words, high FA rate reduced the operator's compliance with automation (compliance was defined as "the tendency to agree with an automated aid when it provides an alert" [Levinthal and Wickens, 2006]). Conversely, when the miss rate was high, performance on a concurrent task was affected more than the automated task, because operator had to allocate more visual attention to monitor the automated task. In other words, high miss rate reduced the operator's reliance on automation (reliance was defined as "the operator's assumption that a system is functioning normally while the alert is silent" [Levinthal and Wickens, 2006]). Similarly, Dixon and Wickens (2006) showed that FAs and misses affected compliance and reliance, respectively, and their effects appeared to be relatively independent of each other. In contrast, Dixon et al. (2007) showed that FAP automation hurt "performance more on the automated task than did miss-prone automation, (e.g., the "cry wolf" effect) and hurt performance (both speed and accuracy) at least as much as MP automation on the concurrent task." FAP automation was found to affect both operator compliance and reliance, while MP automation affected only operator reliance. The authors suggested that the FAP automation had a negative impact on reliance because of the operator's overall reduced trust in the automated system. Similarly, Wickens et al. (2005a) demonstrated a greater cost associated with FAP automation (than with MP automation), which affected both the automated and concurrent tasks.

Lees and Lee (2007) showed that "unnecessary alarms" (i.e., alerts that are legitimate but, due to the peculiarities of the situation, do not require operator's 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 (i.e., utility, predictability, and intent) need to be considered beside the traditional description of alarms according to signal detection theory (i.e., FAP vs. MP). Additionally, Chen and Terrence (2009) showed that there is a strong interaction between the type of automation unreliability and participants' self-assessed attentional control. Overall, it appears that for high-attentional control participants, FAP alerts were more detrimental than MP alerts due to *disuse* of automation. For low-attentional control participants, conversely, MP automation was more harmful than FAP automation due to *misuse* of (i.e., over-reliance on) automation. Their results are consistent with past research (Lee and Moray, 1992; Lee and See, 2004) that self-confidence is a critical factor in mediating the effect of trust (in automation) on reliance (on the automatic system). 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.

Lee and See (2004) characterize human-agent teams in terms of how human teams interact. They define trust as the "attitude that an agent will help achieve an individual's goal in a situation characterized by uncertainty and vulnerability," implying that humans perceive automated systems as a team member, and attitudes of misuse or disuse develop as operators become familiar with the system. This implies that trust is an intrinsic quality depending on the attitude of humans toward automated systems. Much of the previously mentioned results suggest that trust (or calibration) is an extrinsic factor determined by operators' perception of the task environment. However, the research on intent errors and false alarms indicates "trust" decisions are also based on the operators' belief in the importance of personally controlling decision outcomes (Beck et al., 2007; Chen and Terrence, 2009). On a positive note, Beck et al. indicate that a combination of performance feedback and scenario training can reduce both appraisal and intent errors suggesting that different training regimes may be necessary for extrinsic (feedback) and intrinsic (scenario training) sources of automation usage errors.

The intrinsic definition has interesting implications suggesting that humans view automated systems anthropomorphically. This begs the question whether we can design systems not only to perform human-like tasks, but to actually act like humans. For example, if robots can be made to be perceived as human, then teaming relations would not only be more natural but also instinctive and synergistic like a well-honed basketball team. Research to date is sparse but suggestive. Based on their research, Arkin (2007) and his colleagues posit that, in the future, robots can be made not only to react to human cues but to do so in a predictable and human-like manner—even to the extent of developing ethical behaviors. This would allow humans and robots to share mental models of not only the external environment but also each others' models (Endsley and Riley, 2004). However, the research in this area is not mature; hominid robots or even robots that act like dogs can operate successfully only in constrained laboratory or commercial environments. Currently, humans control or monitor unmanned systems as sophisticated equipment rather than as team members, showing more trust in a perceived human peer than a machine peer with the same capabilities (Dzindolet et al., 2001a).

2.3 Situation Awareness

One of the most critical factors for achieving effective supervisory control of multiple UVs is maintaining adequate SA of the overall tasking environment as well as individual UVs. There are three levels of SA as defined by Endsley (1995): (1) perception of data and environmental elements, (2) comprehension of the current situation, and (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. While information updates are needed, recent studies have also shown that interrupting a primary task (i.e., supervisory control of UVs) with an intermittent task (e.g., communication messages) can have a negative impact on SA (Cummings, 2004; Dorneich et al., 2006). For example, Cummings (2004) found that instant messages diverted participants' attention from their primary task (i.e., 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.

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. Participants performed four tasks in this experiment, including target detection and route-planning (primary tasks), a communications task to evaluate SA, and a change detection task. The routes for the UAV and the UGV were preplanned, and the only time the participant controlled the UGV was when it was necessary to navigate around an obstacle in the environment. The primary tasks were interrupted by both the verbal communication task and the change detection task. The latter required participants to indicate each time they noticed that an icon of a target they had previously detected had unexpectedly changed position on a map grid. Half of these changes occurred during a "transient event," when the UGV stopped and its status bar flashed, while the remaining four changes occurred while participants were focused on the UAV monitoring task. Parasuraman et al. found that participants' accuracy at detecting changes related to the position of the target icons was very low, especially during the transient events. Their results suggest that change blindness occurred most frequently when a distracter (a transient event) was present, but it 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 tasking 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 (i.e., intention forming and action planning) as well as the evaluation phases (i.e., 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).

2.3.1 Task Switching

Simultaneous control of multiple UVs may require the operator to switch attention/control among the vehicles from time to time. Basic research on the 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 human-robot interaction (HRI), research has been conducted to investigate the effects of task switching on SA and operator performance (Crandall et al., 2005; Squire et al., 2006; Wang and Lewis, 2007). Squire et al. (2006) studied operators' response time as it related to interface type (options available to the user) and task switching, as well as strategy switching (offensive vs. defensive, in the context of a RoboFlag simulated game). Task switching was shown to slow response time by several seconds, especially when automation was involved. Likewise, Squire et al. found that response time increased by several seconds when participants switched between offensive and defensive strategies. When participants were provided an interface that allowed the flexibility to choose between a fixed sequence of automated actions or selectable waypoint-to-waypoint movement, mission time was reduced in spite of task or strategy switching. Crandall et al. (2005) examined the amount of interaction time vs. noninteraction time, or "neglect tolerance," to develop a predictive model to determine the number of robots (heterogeneous or homogeneous) that may be effectively monitored simultaneously by a single operator, given the requirements of a particular interactive task. Crandall et al. suggested that a predictive analysis such as theirs might be useful in the context of task switching.

2.3.2 Error Diagnosis and Recovery

Frequently, changes in the environment may require the operator to modify his/her plans for the UVs. Muthard and Wickens (2002) evaluated the effects of automation on pilot's 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. 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). 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. In Muthard and Wickens (2002), pilots failed to modify their plans based on environmental changes on nearly one-third of the trials. Plan continuation errors were especially pronounced when there was an unreliable automation aid as compared with no aid present.

2.4 Operator Workload

Perceived workload can impact operator performance in an UV supervisory task relative to the level of automation assigned to the robotic entities being supervised. The level of automation of a robotic entity further influences operator compliance and reliance on the automated robots. Ruff et al. (2002) examined perceived workload and found that when given complex tasks, operators tended to prefer autonomy that provided a LOA exhibiting "management-by-exception" (~level 6 in table 1). Although this LOA produced performance decrements, it lowered perceived workload as participants demonstrated satisficing. In contrast to "management-by-exception," Ruff et al. found that perceived workload increased when participants were subjected to automation that was less than perfectly accurate. Their lack of trust in the automation led participants to take extra time to double-check the system's accuracy in a "management-by-consent" condition (~LOA 3, 4, or 5 in table 1). There are also individual differences associated with perceived workload. For example, Mogford et al. (1995) found that individual operator differences were a mediating factor of perceived mental workload, along with equipment quality and ATC operator strategies, in a model of ATC.

The following sections review research findings in specific areas of supervisory control of UAVs, UGVs, and heterogeneous UVs (i.e., using different types of UVs in the same mission).

3. Supervisory Control of Unmanned Aerial Vehicles

Two often-used methods of supervisory control of UAVs are management by consent (MBC) and management by exception (MBE), which have been researched extensively in the manned aviation environment (Olson and Sarter, 2001). MBC requires the automation to ask for explicit consent from the human operator before taking any actions; MBE, on the other hand, allows the automation to initiate/perform actions unless overruled by the human operator. In their survey of airline pilots, Olson and Sarter (1998) found that MBC was preferred by most pilots under normal circumstances, as it gave them more control over the automated systems. However, MBE was preferred when the pilots were under time pressure and higher workload, or when the task was highly complex or of low criticality. Olson and Sarter (2001) conducted a simulation experiment to further examine pilot performance when interacting with MBC systems. The results showed that, under time constraints, pilots often had difficulty detecting conflicts before giving consent to the automation, especially when the automation did more than expected by the pilots.

Comparisons of the effectiveness of MBC and MBE were also conducted in the unmanned aviation environment (Cummings and Mitchell, 2006; Ruff et al., 2002, 2004). Ruff et al. (2002) evaluated the effects of LOA, decision-aid reliability, and number of UAVs under control (one, two, or four) on the human operator's target acquisition task performance. They found that, overall, an MBC-type decision aid provided the highest mission efficiency (i.e., total number of targets destroyed divided by the total number of missiles fired) and resulted in the best survivability performance (i.e., number of UAV hit points sustained). However, the authors reported that automation level interacted with number of UAVs controlled and reliability of decision aid for the other measures such as SA, perceived workload, and trust in the automation system. They found that SA was highest in the MBC condition, followed by manual operation, and finally the MBE condition. As the number of controlled UAVs increased, SA degraded for all three LOA conditions, with the manual condition having the most severe degradation. Furthermore, the higher the LOA, the more benefit of vigilance and workload relief it provided during complex tasks (when the number of UAVs increased and/or when reliability decreased). For example, in the MBC condition at 95% reliability, participants experienced higher workload (compared with the MBE condition) as a result of double-checking to be sure the automation was accurate. In the context of trust in the system, researchers found that it increased in both the MBC and the manual conditions as the number of UAVs increased when reliability was perfect, with the MBC providing the most trust. However, when the reliability was not perfect (i.e., 95% reliable), both MBC and MBE resulted in lower trust ratings as the number of UAVs increased.

Ruff et al. (2004) conducted another study to compare the effectiveness of MBC and MBE systems in a UAV control setting (two or four UAVs). In this study, the MBC system proposed route replans and target identifications. The MBE system, on the other hand, automatically implemented proposed actions after a predetermined time period, unless the operator overruled. Overall, regardless of experimental condition, participants did not utilize the automation aiding system much at all. When under greater time constraints, they utilized it more often but still rarely. As contrary to the Ruff et al. (2002) study, MBC did not result in significantly better performance than MBE. However, with MBE, participants' perceived workload increased as time pressure increased. With MBC, in contrast, perceived workload remained at a similar level with an increased time constraint. In other words, although MBE was hypothesized to reduce workload under high time pressure, the opposite was found.

Cummings and Mitchell (2006) investigated LOA in the context of controlling four UAVs for target acquisition tasks. The LOAs employed in the study roughly corresponded to levels 1, 2, 4, and 6 in Parasuraman et al. (2000). The level of replanning required in reaction to unexpected events was also manipulated (high vs. low). They found that under the high replanning condition, operators performed the worst with the "active" level automation (corresponding most closely to MBC). The authors described this performance decrement as "cognitive saturation" and observed that operators were unable to correctly assimilate data from various sources, weigh uncertainty in the solution space, and prioritize their tasks. Operators had the highest level of level-1 SA (i.e., perception) and level-2 SA (i.e., comprehension) with the "super-active" level automation (i.e., MBE) but not the level-3 SA (i.e., future projection). In fact, operators exhibited automation complacency and erroneously destroyed more targets than they did when using automation with lower LOAs. This finding of complacency is consistent with what has been reported in the literature and is an important issue that user interface designers of automation systems need to consider (Chen and Joyner, 2009; Parasuraman et al., 1993; Thomas and Wickens, 2000; Young and Stanton, 2007).

Levinthal and Wickens (2006) also investigated the effects of imperfect automation on robotics operator's target detection performance when controlling multiple (two or four) UAVs. This study compared Meyer's (2001) independence hypothesis (which posited that FAP and MP automations have qualitatively different effects on operator dependence on the automated systems) to the model that FAP automation hurts more than MP automation. Their results were in favor of the independence hypothesis as participants in an MP condition (i.e., 60% reliability with 3:1 likelihood of misses over FAs) showed an increase in compliance and a decrease in reliance whereas participants in an FAP condition (i.e., 60% reliability with 3:1 likelihood of false alarms over misses) showed a decrease in compliance and an increase in reliance. However, it was found that FAP aids resulted in delayed response times compared to the MP aids and 90% reliability aids. The authors, therefore, concluded that FAP aids, overall, were more disruptive to operator performance than were MP aids.

Some researchers examined operator performance and workload in control of large numbers of UAVs (Galster et al., 2006). For example, Miller (2004) modeled the operator workload whose task is to authorize weapon release for targets identified by UAVs. His model shows that, under anticipated target densities, the operator would become overloaded when controlling 13 UAVs, even if the weapon release authorization is the only task the operator has to perform. In an empirical study, Galster et al. (2006) examined operator performance in a supervisory control task of four, six, or eight UAVs. Overall, participants performed well on their primary task (selecting the correct targets and the highest-priority targets to process). Results suggested that although the increase in number of UAVs slightly impacted performance (negatively), the number of targets (not the number of UAVs) had a higher impact on perceived workload. Secondary (monitoring) task performance, on the other hand, was significantly worse for the eight UAV conditions than for the four and six UAV conditions.

4. Supervisory Control of Unmanned Ground Vehicles

Supervisory control of multiple UGVs has been examined in contexts of search and rescue tasks (Wang and Lewis, 2006; Wang et al., 2009) and other exploration and reconnaissance tasks (Trouvain et al., 2003; Trouvain and Wolf, 2002). Olsen and Wood (2004) proposed an equation to calculate fan-out (FO: the number of robots a human operator can control simultaneously [i.e., span of control]) based on activity time (AT: the time that a robot is active) and interaction time (IT: the time that it takes for a human operator to interact with a robot). The authors also conducted four simulated experiments to test the equation. Results showed that when 18 robots were available for a target search task, FO for the type of robots with the highest autonomy was as high as 9 for the less cluttered tasking environment (compared to 5 in the more cluttered environment). Olsen and Wood concluded that their FO equation could accurately model operator span of control in many cases; however, FO might change due to other task characteristics and complexities in the environment.

Riley and Strater (2006) investigated navigating two UGVs through a maze while manipulating the control mode (serial, parallel, and two parallel conditions involving manual control of one robot and a varying LOA in the second, supervised robot). SA, workload, and performance navigating the robots as well as monitoring performance were assessed. Monitoring performance was positively correlated with SA scores, and participants in the serial control condition exhibited slightly higher SA scores than the parallel conditions. However, the parallel control condition resulted in the best navigation performance and the lowest perceived workload.

Participants in Chadwick's (2006) study were responsible for controlling one, two, or four semi-autonomous UGVs simultaneously. Operators were assessed on monitoring, responding to cued decision requests, and detecting contextual errors, the latter of which occurred when the robot was performing correctly but inappropriately, given contextual or environmental factors. In the case of a contextual error, the robot cannot recognize such a malfunction, so the operator must take notice of it; one example may be failed navigation, in which the robot would need to be redirected to a more optimal path. Participants were required to monitor and recharge robots' batteries, attend to targets, and detect and redirect navigation errors. Operator performance varied depending upon the cognitive demands of the various tasks. Degradation was found to come from "event time-line conflicts" and attentional limitations, the latter of which were most prevalent in the contextual error identification and redirecting task.

In Trouvain and Wolf (2002), participants used either two, four, or eight simulated UGVs to perform inspection tasks at the predesignated inspection locations. Results showed that participants' overall task performance (i.e., number of inspections completed) improved from the two- to four-robot condition but not from the four- to eight-robot condition. However, their data also showed that when the number of robots increased from two to four, the average inspection delay (i.e., amount of time robots spent on waiting for human inspection after reaching the inspection locations) also more than doubled. In fact, it was found that participants had difficulties keeping more than two robots active at the same time. The subjective workload data also showed that participants experienced slightly higher workload when the number of robots increased from two to four; however, they experienced significantly higher workload when the number of robots was eight.

Wang and Lewis (2006) explored operator demands of autonomous robot teams vs. manually controlled robot teams in a building search task. In this within-subjects experiment, three robots were controlled serially, so only the selected robot would accept commands. Participants controlled waypoint movements, manually teleoperated the robots, and operated a camera (panning and tilting it to achieve an optimal view). Waypoint and teleoperation control improved in the autonomous condition, but camera control did not differ. Participants also switched control between the three robots more frequently in the autonomous mode than in the manual control mode. Results further showed that autonomous cooperation between robots aided operator performance. Wang and Lewis believed that this was because their search task consisted of several subtasks, which participants had to interact with during the windows of their "neglect time" (see Crandall et al., 2005). Switching control between the robots more frequently (as in the autonomous mode) gave participants more time to finish the subtasks involved (Wang and Lewis, 2006).

In a follow-on study, Lewis and his colleagues (Wang et al., 2009) investigated operators' performance when they controlled 4, 8, or 12 robots (within-subject variable) for a victim-search task. The results showed that in the full-task control condition (participants implemented waypoints for the robots and controlled the cameras), operators performed better (i.e., found more victims) with 8 robots compared with 4 and 12 robots. Operators' perceived workload, however, increased monotonically with the number of robots. Wang et al. (2009), therefore, concluded that somewhere between 8–12 robots seemed to be the limit for direct human control. The authors also suggested that automation of navigation-related tasks (e.g., path-planning) seemed to be more important than "efforts to improve automation for target recognition and cueing" in the context of controlling a large team of robots.

5. Supervisory Control of Heterogeneous Unmanned Vehicles

Future warfare employing the Future Combat System (FCS) may need to integrate information from multiple platforms, potentially from both aerial and ground sources. UAVs generally provide exocentric views of the problem space (i.e., the battlefield), while UGVs present viewpoints that are egocentric and immersed in the environment. The ideal view depends on the task; overall awareness and pattern recognition are optimized by exocentric views, whereas the immediate environment is often viewed better egocentrically. Displays for integrating information from different frames of reference (e.g., exocentric and egocentric) present potential human performance issues that need to be carefully evaluated (Thomas and Wickens, 2000). Research has shown that integrating information across egocentric and exocentric views can be challenging for the operator (Olmos et al., 2000; Thomas and Wickens, 2001). Essentially, dual displays with both frames of reference require effective scanning of the displays and integrating information from two different perspectives to form an accurate assessment of the situation. Furthermore, operators may be susceptible to a saliency effect and anchoring heuristic/bias (Thomas and Wickens, 2000). In other words, salient information on one display may catch most of the operator’s attention, and the operator may form an inaccurate judgment because information from the other sources are not properly attended to and integrated. In Thomas and Wickens (2000), participants were found to tunnel their attention into the egocentric view to the exclusion of information from the exocentric view.

Chen et al. (2008) simulated an FCS-like command vehicle environment and had the participants perform a target designation task with a semi-autonomous UAV and a semi-autonomous UGV, teleoperate a UGV, or, in the mixed condition, control all three assets. They found that when the operator could use all three assets, they tended to ignore the equally efficacious UGV and relied on the UAV. This agreed with other U.S. Army–sponsored research using gaming technology showing the counterintuitive result that even when participants performed better with UGVs, they still preferred UAVs (Luck et al., 2006). This may indicate a generalized preference for the god’s-eye exocentric view afforded by the UAVs in comparison to the egocentric views obtained from the UGVs.

Billman and Steinberg (2007) described a set of HRI performance metrics for the evaluation of mixed-initiative heterogeneous robots (i.e., 5–10 air, sea, and undersea UVs). They found that these metrics were useful in understanding collaboration between human operators and heterogeneous robots. The metrics included planning time, task time, SA, operator workload, operator assessment of the usability of the systems, and mental model mapping (between reality and the operator’s temporal and spatial mental model of the system state). Lessons learned from a series of human-in-the-loop experiments were documented, and recommended modifications of the metrics were also presented.

In the following section, we review innovative techniques and technologies designed to enhance operator performance of supervisory control of UVs.

6. Interface Designs for Supervisory Control of Unmanned Vehicles

When conducting supervisory control research, the interface design must support effective interactions and provide good usability, or the design itself may affect perceived workload and overall performance. For instance, Cummings (2004) found that intermittent messages from a chat communication tool interrupted primary task performance. This finding demonstrates how the presentation of alerts and alarms can be important in both experimental and "real world" system interfaces, as alerts and alarms may impact overall operator performance in unexpected and negative ways if they are designed as independent features of the system. Some methodologies for interface design have been investigated in the context of complex supervisory control tasks, including abstraction hierarchy and cognitive task analysis (Linegang et al., 2006; Nehme et al., 2006). For example, Linegang et al. (2006) applied the abstraction hierarchy approach to design a novel system. This approach allows an interface designer to decompose a system into subcomponents that may each be analyzed in terms of how to best apply automation to best aid the user. Additionally, Nehme et al. (2006) examined how cognitive task analysis could be mixed with SA criteria to determine a list of requirements for interfaces of future technologies.

Olson and Wuennenberg (2001) presented a list of recommended user interface design guidelines for supervisory control of UAVs. The recommendations included the following:

1. Automation behavior (e.g., system status/mode, system goals, and flight control functions) should be highly visible to the operator. (Rationale: operators tend to be "out of the loop" when systems are highly automated, and they often find it difficult to understand system behavior due to system complexity, coupling, and autonomy.)

2. It should be easy for the operator to extract meaning from the display quickly—minimize information access costs by highlighting relevant information, integrating dimensions, and displaying information in appropriate formats. (Rationale: operators often find it difficult to understand system behavior due to system complexity, coupling, and autonomy.)

3. Display/highlight projected changes and predicted information based on operator inputs, and direct operator attention to the relevant areas. (Rationale: changes to system behavior may be difficult for the operator to visualize or detect.)

4. Provide a quick and easy way to reinstruct automated systems. (Rationale: highly automated systems tend to be difficult to reprogram, and manual control may not be an option.)

In a recent study, Nam et al. (2009) applied human-computer interaction principles to the design of a multiagent system interface. When a user-centered design approach was used, three interface types were designed and tested. Each interface satisfied a set of design goals, including (1) one window display of relevant information, (2) user-friendly layout, (3) displaying only essential information for decision making, (4) providing rapid user interaction, (5) providing necessary and essential information for dynamic role changing, and (6) providing feedback. Nam et al. concluded that interfaces for multiagent systems are efficient when they are compact and when they accentuate information that aids in the decision-making process. Based on the results, guidelines for multiagent interface design were proposed.

Adaptive automation can be a very useful tool to aid operators with supervisory control tasks as it can "leverage the strengths of humans and computers to improve overall system performance while mitigating the negative aspects of both" (Cummings, 2004). More information on adaptive automation and other potential user interface designs for supervisory control of unmanned vehicles will be discussed in section 5.6.

Finally, within the context of H-A teaming, interface design techniques should focus on supporting team processes between the human supervisor and the UVs. As mentioned previously, team processes can be supported by identifying team behaviors that will occur during the task. For interface design, the goal would be to identify characteristics of the interface that could support the team processes that emerge from the H-A team's behaviors. For example, if shared awareness emerges, then the interface should support communication methods that will facilitate a shared understanding among the team. This approach to interface design could be referred to as a team-centered interface design approach. Designing an interface using a team-centered approach may enhance the robustness of the interface and facilitate the management of workload through a balance between task and interaction workload (Saget et al., 2008).

It is important to note that designing an agent's interface that supports team processes will not alone lead to effective team interactions; both the human and the agent are jointly responsible for developing team play (Endsley, 1995; Fan et al., 2008). In Fan et al.'s (2008) collaboration model of an H-A team, agents can work autonomously until they run into a problem, at which time they could query the human. The active role of the human within the H-A team, therefore, requires attributes that allow the human to accept/exploit an agent's capabilities. For example, an agent may support coordination among team members, yet whether the human accepts the agent's attempt to coordinate may depend on the human's trust in the agent. Trust may be established through an understanding of the agent's abilities and reliability (Lee and See, 2004; also see section 2.2). Therefore, developing team play within H-A teams requires consideration of not only the agent's capabilities and attributes, but also the human's knowledge, skills, abilities, and attitudes.

6.1 Multimodal Displays/Controls

Remote perception is essential for effective teleoperation. In teleoperating environments, human perception is compromised because the natural perceptual processing is decoupled from the physical environment. This decoupling affects people's perception of affordances in the remote scene and can have a detrimental effect on situational awareness and, therefore, the overall effectiveness of the robotic's task performance (Woods et al., 2004). The performance degradations can be further exacerbated due to less-than-ideal video quality (Chen et al., 2007; Chen and Thropp, 2007). Simpson et al. (2004) proposed using a spatial audio display to augment UAV operator's SA and discussed its utility for each of the three SA levels. They recommended that both visual and spatial audio information should be presented concurrently. They also suggested that presenting the audio information spatially may enhance UAV operator's sense of presence (i.e., telepresence). However, the link between presence and task performance has yet to be established. Additionally, spatial audio displays can be ineffective in a noisy environment, and the user may experience front-back confusion. Tactile displays, therefore, present a viable alternative to audio displays. Haas et al. (2009) designed a Soldier-swarm display (the swarm consisted of 40 ducted fan aircraft) and compared its effectiveness when information was displayed using visual, auditory, and tactile combinations. The multimodal displays (compared with the visual display baseline) significantly improved Marine participants' detection performance (i.e., reduction in response times) and decreased their perceived workload. In another study, Gunn et al. (2005) compared the effectiveness of a sensory display and a cognitive display for presenting warning information in a UAV control task. They found that the sensory display (which presented the information by changing the physical attributes of stimuli) resulted in more threat detections, fewer false alarms, faster response time, and a lower perceived workload than did the cognitive display (which required symbolic manipulations to define critical signals). Gunn et al. also compared the utility of different types of directional cueing interfaces (visual, spatial audio, and haptic) and found no differences in their effectiveness. For a comprehensive review of multimodal displays and controls for robotics control, please see Chen et al. (2007).

6.2 Planning Tools

Planning (e.g., route-planning task) is a vital part of human-robot interaction. It is increasingly common for plans to be generated by automated/intelligent systems in mixed-initiative operations. However, lessons learned from a U.S. Naval Intelligent Autonomy program indicated that human operators sometimes questioned the accuracy and effectiveness of automated plans (Linegang et al., 2006). Specifically, some human operators indicated that they had difficulties understanding the rationales for some plans and how the plans were generated (Linegang et al., 2006). Additionally, some operators reported that they had difficulties trying to specify mission parameters (e.g., goals and constraints) in the way required by the automated planning system (Linegang et al., 2006). 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. Therefore, effective communication between the human operator and the robots is critical in ensuring planning effectiveness and mission successes.

Research has been conducted on ways to enhance human-robot communication (Stubbs et al., 2008). For example, Stubbs et al. demonstrated the effectiveness of a robot proxy to enhance shared understanding between the human operator and the robot in an exploration task. The communication mechanism was based on a common ground collaboration model and was able to improve the human operator performance in the following areas: more accurate plans, more efficient planning (fewer times of replanning), more efficient and faster task performance, and better mental model of the robots' capabilities. The U.S. Navy has also sponsored a research and development program to design a mission-planning tool for human operators controlling a heterogeneous group of robots (Linegang et al., 2006). The tool, Mission Displays for Autonomous Systems (MiDAS), uses an ecological approach to reduce conflicts between human operators and the automated planning system.

6.2.1 Schedule Management Aid

When controlling multiple semi-autonomous UVs, each executing its own predetermined plan, the operator may experience high workload when more than one UV needs his/her attention at the same time. It is therefore beneficial to let the operator know when potential processing bottlenecks may occur so that they can make arrangements to mitigate the bottleneck if necessary. Cummings et al. (2007) designed an intelligent schedule management aid and tested its effectiveness in a simulated suppression of enemy air defenses mission environment with four UAVs. The aid incorporated timeline displays that show potential bottlenecks, and it also presented potential scheduling conflicts using configurable displays (figure 1). Overall, both the timeline and the configural displays were effective. However, the authors cautioned that in order for the displays to be effective, the user interface designers need to ensure the following:

1. The information's importance matches its representation salience. (Rationale: overly salient representations may cause the operator to fixate on something not important while overlooking more serious issues.)

2. The aid presents useful solutions to emerging problems rather than simply providing visualizations of potential problems. (Rationale: Cummings et al. showed that only presenting visualizations without solutions was not more effective than no visualizations.)

Dorneich et al. (2006) took a different approach and used neurophysiological sensors (electroencephalography [EEG]) to detect cognitive workload in a navigation task (i.e., walking along a familiar route) with an intermittent communication task and mathematical interruption

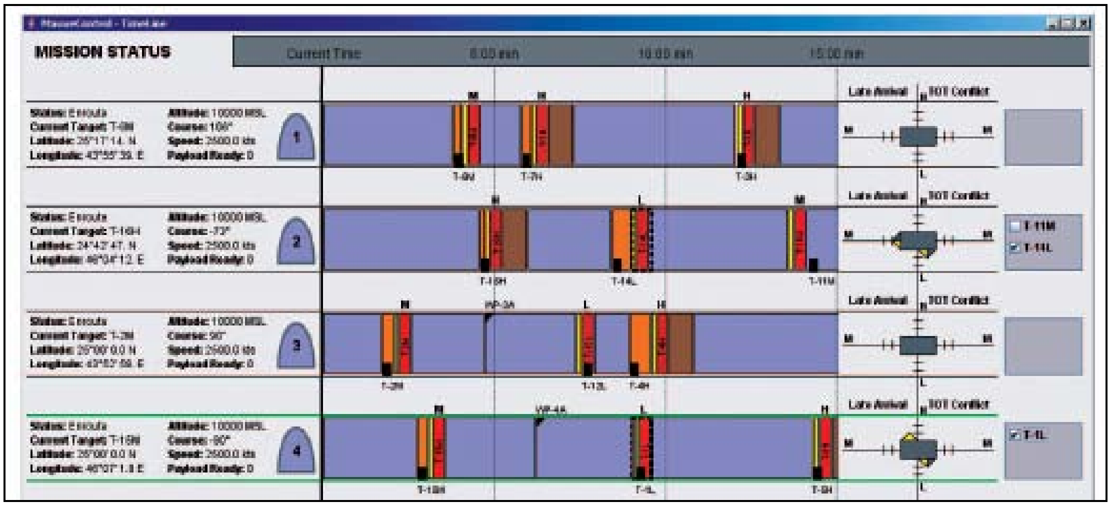

Figure 1. Timeline display and configural display (right) (adapted from Cummings et al. [2007], with permission).

task. Throughout the experiment, EEG sensors accurately evaluated cognitive workload about 70% of the time, and a communication scheduler adapted task scheduling information by informing the participant what to focus on next. The communication scheduler positively impacted participants' performance by rescheduling their priorities, resulting in only a temporary loss of SA for low-priority messages (Dorneich et al., 2006).

6.3 Visualization Tools

Humphrey et al. (2006) examined the use of visualizations as an aid for operators responsible for controlling a team of robots. Previous studies examined color-coding robot status and team associations; this study added shapes to represent an individual robot (condition 1), or teams of robots (condition 2 [semitransparent] and condition 3 [solid]) (figure 2). Participants were tasked with selecting specific robots relative to other robots or environmental characteristics, and to verbally confirm or deny accuracy of statements regarding a robot's status. Investigators were interested in the level of operator engagement, as indicated by the frequency with which participants utilized the visualizations. Results indicated that the semitransparent and solid visualizations were preferred and utilized significantly more than the individual visualization. Participants slightly preferred (in a posttrial questionnaire) the presentation of both an individual and semitransparent visualization (in the same trial). The authors plan to continue this research with the hypothesis that an operator's SA will increase when visualization techniques are applied to managing teams of robots; this technique may also help an operator supervise a larger team of robots.

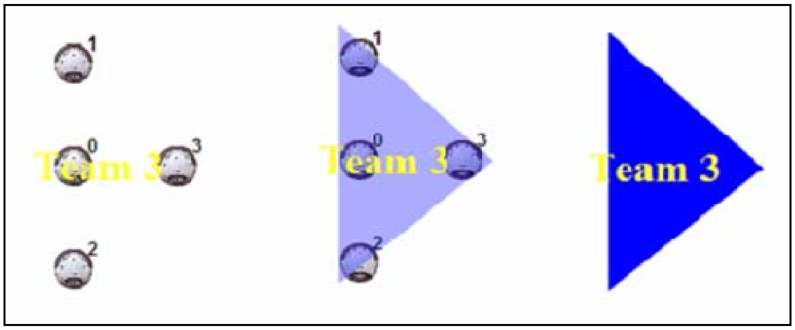

Figure 2. Visualization tool (from left to right): individual robots, semitransparent, and solid (adapted from Humphrey et al. [2006], with permission).

6.3.1 Augmented Reality

Augmented reality (AR; 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; Calhoun et al., 2006; Draper et al., 2006; Kramer et al., 2005). For example, the U.S. Air Force has identified several candidate synthetic vision overlay concepts for UAV applications (Calhoun and Draper, 2006) (figure 3). The following information (potentially) can be overlaid graphically on the streaming video: maps and other synthetically generated symbology, photoimagery, terrain elevation, laser range scans, past and potential future robot paths, updates via networked communication with other sources, and other vital statistical data (Baker et al., 2004; Calhoun and Draper, 2006; Collett and MacDonald, 2006; Daily et al., 2003; Keskinpala and Adams, 2004). However, large amounts of information, although helpful in reducing the operator's scanning effort by providing more data in a centralized area (i.e., the video), can create visual clutter and degrade operator's information processing (Calhoun et al., 2005). Thus, it is important that a declutter capability be provided so the operator can customize the overlaid information presentation according to the situation and tasks.

More research is needed to determine the optimal approach to decluttering (i.e., global approach by deselecting classes of information or local approach by deselecting individual symbology [Calhoun et al., 2005]). Additionally, overlaying information on a video feed can potentially lead to cognitive tunneling, as the operator's attention can be captured by the overlaid data while important elements/developments in the video might be overlooked (Kramer et al., 2005; Tufano, 1997; Wickens, 2005). However, a more recent study by Iani and Wickens (2007) indicated that the attentional tunneling effect of the AR displays may not be as pronounced as previously suggested. The tradeoff between adding information to the video feed and cognitive tunneling needs to be more systematically evaluated. A list of human factors issues with UAV AR systems and their potential solutions can be found in Calhoun et al. (2005).

Figure 3. Synthetic vision symbology added to simulated UAV gimbal camera video, marking threat, landmarks, areas of interest, and runway (symbology generated with LandForm SmartCam3D, Rapid Imaging Software, Inc.; adapted from Calhoun and Draper [2006], with permission).

6.3.2 Ecological Interface Design

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 and Rasmussen, 1992). 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 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 nonintegrated 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 (2003) 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 (figure 4) and compared its effectiveness with that of an EID display without intention indicators of the automated system (figure 5). 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

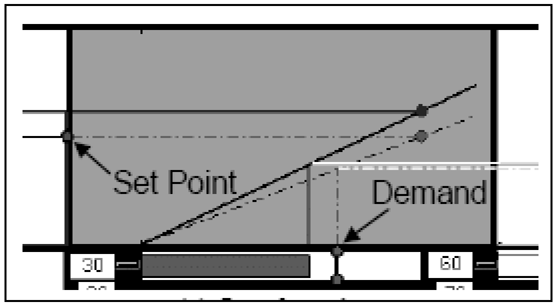

Figure 4. EID display that shows the intention of the automated system (dotted lines indicate the automation's intentions) (adapted from Furukawa et al. [2004], with permission).

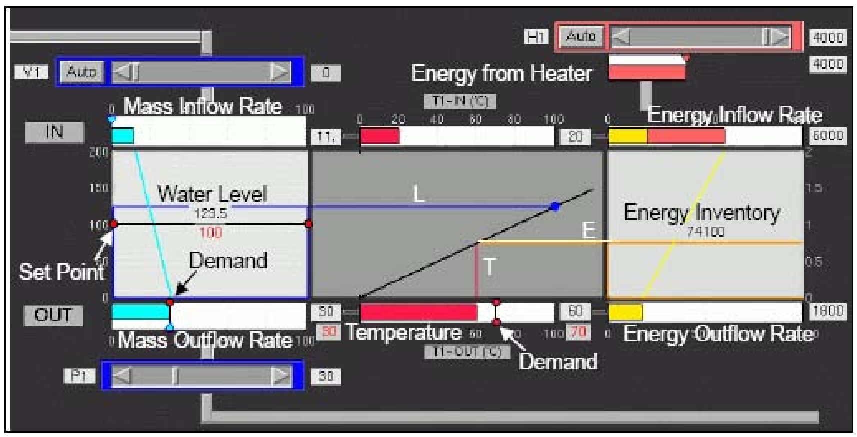

Figure 5. EID display (the three panels in the center) for a partially automated process control simulation.

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.

Cummings and Bruni (2009) designed a user interface that supports a single operator's ability to control four UAVs simultaneously. They utilized visualization techniques in designing a tool that helps the operator replan the mission. For example, they used a configural display to depict the overall cost of the revised plan (figure 6). Furukawa (2008) also incorporated an EID display into a RoboFlag simulation program. The results showed that the EID display enhanced the human operator's performance of supervising a team of robots by portraying essential functional information (i.e., graphical representation of the offensive and defensive functions for the RoboFlag simulated game). A detailed review of the EID—the empirical evidence of the efficacy of EID, why EID improves operator performance, how EID can be leveraged, and challenges of implementing EID—can be found in Vincente (2002).

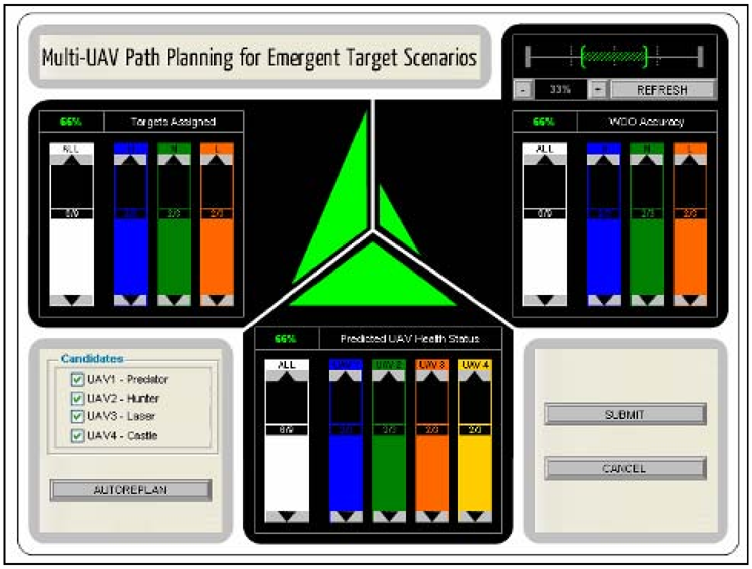

Figure 6. Supervisory control of four UAVs—configural display is the center panel with three green triangles indicating the costs of planned operations (image adapted from Cummings and Bruni [2009], with permission).

6.4 Attention Management Tools (Interruption Recovery Aid)

When controlling multiple robots at the same time, it is inevitable that the operator will tend to 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 he or she was 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 et al. demonstrated that by simply 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. discussed the utility of an SA recovery tool (named CHEX, figure 7) that displayed a textual event history list in a naval air warfare environment (i.e., monitoring a geoplot of an airspace that contained ownship and ~50 other aircraft). St. John et al. found that CHEX was more effective in helping the operator resume his or her task after interruptions (i.e., blank screen lasting either 30 or 120 s) than a video replay tool, which was worse than the baseline condition (i.e., no aid). CHEX presented changes in a table and linked them to the map when the operator selected a change from the table. However, Scott et al. argued that the ineffectiveness of the video replay tool shown in St. John et al. might be improved if a better design had been adopted.

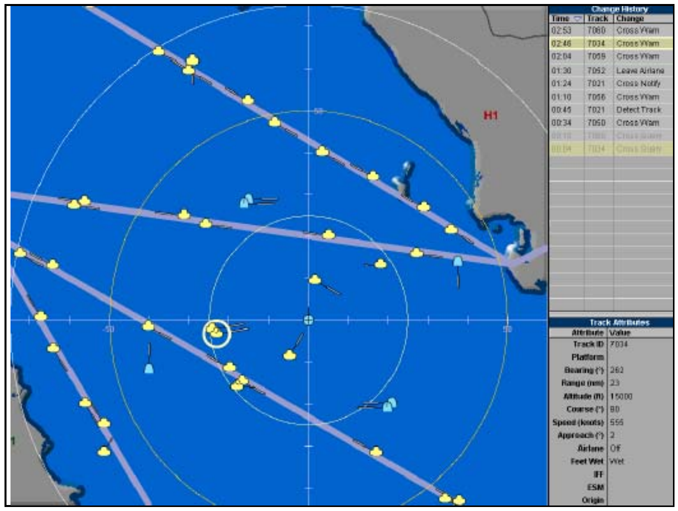

Figure 7. Interruption recovery aid—textual event history list (CHEX, upper right) (adapted from St. John et al. [2005], with permission).

Scott et al. presented two types of replay tools—one replayed the events at a 10 × real-time speed, and the other presented bookmarks on the event timelines and the operator could view the replay by selecting the bookmarks (figure 8). Results showed that both replay techniques were effective, especially when the tasking environment was challenging. Based on the results, the authors recommended the following design guidelines for interruption assistance interfaces:

1. Enable user control of event replay.
2. Provide visual summary of critical events.
3. Limit visual summary to goal-related events.
4. Clearly indicate relationships between past and current system state.

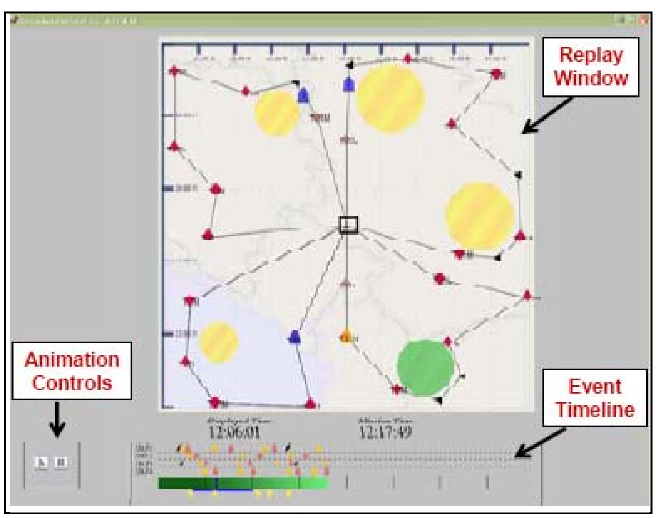

Figure 8. The interruption assistance interface (adapted from Scott et al. [2006], with permission).

6.5 Trust Calibration Tools

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. 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. Rovira et al. (2007) investigated the differential effect of automation reliability and different types of automation (i.e., decision support and information support) on performance during a command and control task. Their results confirmed a differential cost of automation unreliability for three forms of decision automation, as compared with information automation when the overall automation reliability was at 80%. At 60% overall automation reliability, however, there was a reduction in performance for both information and decision automation during unreliable trials. This finding suggests that the type of automation employed is irrelevant when automation reliability is below a certain threshold. Based on their findings on the different types of automation, Rovira et al. suggested that decrements in decision-making performance will be lower when operators can query the automation, inspect raw information sources, and verify or negate the automated advice.

In another study, Seppelt and Lee (2007) designed a display based on EID that portrayed graphically the capabilities and limitations of the adaptive cruise control of a vehicle for a driving task in different 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. Lee and See (2004) developed the following guidelines on designing systems that promote appropriate trust in the automation:

1. Design for appropriate trust, not greater trust.
2. Show the past performance of the automation.
3. Show the process and algorithms of the automation by revealing intermediate results in a way that is comprehensible to the operators.
4. Simplify the algorithms and operation of the automation to make it more understandable.
5. Show the purpose of the automation, design basis, and range of applications in a way that relates to the user's goals.
6. Train operators regarding its expected reliability, the mechanisms governing its behavior, and its intended use.
7. Carefully evaluate any anthropomorphizing of the automation, such as using speech to create a synthetic conversational partner, to ensure appropriate trust.

6.6 Adaptive Automation

Adaptive systems were developed more than 50 years ago to aid the operator by keeping performance constant as a function of task difficulty (Kelley, 1968). One of the early paradigms used queuing theory as an allocation system to service aviation tasks on which the operator was performing poorly during high workload situations. More recently, adaptive automation has been proposed as a technique to keep operators engaged in a multitasking situation without overwhelming them during peak workload situations (Barnes et al., 2006a; Rouse, 1988; Parasuraman et al., 1992). These systems, a middle ground between fully automated and manual control, provide a means of keeping operators in the loop. The basic concept consists of decisions rules for the computer invoking automation during high workload and for reinvoking manual control during lower workload mission segments. The purpose of the adaptive automation is to keep operator performance within acceptable levels while maintaining attentional focus on important tasks. Decision tasks, in particular, should be completely automated with extreme care because even with perfectly automated tasks, the operator may lose SA if the environment changes or unexpected emergencies occur (Barnes et al., 2006a; Parasuraman et al., 2007; Rovira et al., 2007). For imperfect automation, the situation is worse. Even for highly accurate automated aids, operators tend to over-rely on the automated solution, which can cause even obvious errors to be missed (i.e., automation paradox [Rovira et al., 2007]). Consequently, with less accurate aids, automation itself can be a detriment (Wickens et al., 2006). Therefore, important issues with adaptive systems such as type of invocation process, switching rate, and engagement time must be taken into account in the design of these systems.

Invocation rules (i.e., when to invoke automated or manual control) can be based on models, performance levels, physiological changes, or some mixture of them (Parasuraman et al., 2007). A number of physiological measures have been used to covertly monitor operator’s workload state: EEG, event-related potential, heart rate variability, functional magnetic resonance imaging (fMRI), and combinations of the measures (Barnes et al., 2006a; Scerbo et al., 2001). Freeman et al. (1999) showed the potential of using an adaptive system for human tracking performance using three neurophysiological EEG indices for automation invocation. To test whether EEG was a good indicator of performance, the authors compared two methods for invoking automation: high arousal components of the EEG (high ratios of the beta wave components divided by theta and/or alpha components) and components associated with low arousal (higher ratios of alpha and theta wave components). As predicted, conditions that used EEGs with high beta ratios resulted in better tracking performance indicating that neurophysiological indices could provide a potential means of covertly measuring the operator’s arousal level for adaptive processes. Milkulka et al. (2002) showed similar patterns of performance for a vigilance task using the high beta weightings of the EEG to control adaptive event rate procedures. However, because yoked participants (adaptive processes not based on the operator’s EEG) performed as well as participants in the high beta ratios conditions, it is possible that task difficulty measures may be as efficient as EEG indices for invoking automated processes. They also reported that an automation switching rate of about 15 s between conditions was sufficient for operators to be able to focus on the current task and to adjust to new adaptive conditions.

Wilson and Russell (2007) developed a more sophisticated adaptive automation invocation method using multiple physiological indices that were performance weighted using a neural network–based algorithm. The adaptive conditions resulted in better performance than manual conditions. More importantly, the weights based on the individual's past performance resulted in better performance than group-weighted invocation methods indicating their indices were sensitive to individual differences. All three studies (Freeman et al., 1999; Milkulka et al., 2002; Wilson and Russell, 2007) showed that physiological indices were potential invocation methods for adaptive processes; they also indicated that fairly short switching rates were feasible. Moreover, the Wilson and Russell study indicated that the measures should be tailored to individual differences (see also the Dorneich et al. [2006] study discussed previously). However, none of these studies actually showed an advantage for adaptive processes compared to static automation, nor did they compare physiological to nonphysiological indices.

Parasuraman et al. (1996) demonstrated the efficacy of adaptive processes in a multitasking aviation environment. There were three conditions: static automation, model-based adaptive automation (mission segments with high task difficulty), and performance-based adaptive automation (operator error rate–determined invocation). Manual control was invoked in the middle of the 90-min experiment for the two adaptive conditions. The adaptive system increased the SA of the operators and showed significantly better instrument monitoring performance compared to the static automated conditions for the sessions immediately following the manual conditions. The authors interpreted this as indicating that putting operators in the loop, even briefly during a 90-min experiment, increased their awareness compared to automating a system for the entire 90 min. Also, the experiment demonstrated that either model-based or performance-based rules could be used as invocation triggers for automation.

Parasuraman et al. (2009) compared performance-based adaptive automation, static automation, and manual target identification using an automatic target recognition (device in the automated conditions. Their study employed a multitasking environment involving targeting with UAVs and planning UGV routes. The trigger for adaptive automation was the number of missed changes in a situation map, which suggests that adaptive processes can be invoked from secondary, as well as primary, task difficulties. The results were dramatic—SA, workload, and performance on the secondary task were all improved by automation, but more importantly, performance gains for the adaptive (performance-based) vs. static (model-based) automation were substantial. Based on this study and a review of the literature, Parasuraman et al. (2007) suggested the following guidelines for adaptive automation:

1. Information displays should adapt to the changing military environment.
2. Software should be developed to allow the operator to allocate automation under specified conditions before the mission (as in the Rotorcraft Pilot's Associate [Dornheim, 1999]).
3. At least initially, adaptive systems that do not take decision authority away from the operator should be evaluated. This can be accomplished in two ways:
    a. An advisory asking permission to invoke automation (i.e., management by consent).
    b. An advisory that automation will be invoked unless overridden (i.e., management by exception).
4. For safety or crew protection situations, specific tactical or safety responses can be invoked without crew permission.

Steinhauser et al. (2009) also provided several design guidelines for implementing adaptive automation based on their review of empirical research on adaptive automation and aiding in the past three decades. The guidelines are as follows:

1. Adaptive function allocation to the operator should be used intermittently. Intermittent allocation can improve performance in monitoring tasks.
2. Energetic human qualities should be considered in design. For example, degrees of challenge can be automatically adjusted with artificial tasks.
3. Emotional requirements of the human operator must be considered. The human operator should not feel unnecessary to the system as a whole.
4. The system should be calibrated to the individual operating it. Individual differences factor into the human operator portion of a human-system pairing and thus should be incorporated into the design.
5. Task transformation should be used to simplify tasks for operators. A task that is partitioned and transformed can be handled piecemeal instead of as a whole.
6. The environmental context of the system should be used to determine allocation. Environmental stressors such as heat, vibration, and gravitational force affect human performance and should be addressed.
7. Tasks should be partitioned when both the human and the system can contribute effectively. A true human-system collaboration operates as a pairing instead of a dichotomy of effort. Performance is improved when the most effective attributes of each part are employed.

8. Adaptation should be controlled by the system but be open to human intervention when the system fails to recognize new conditions or demands. In order to reduce task load on the human operator and improve general performance, the system should allocate tasks. To improve satisfaction and motivation, the human operator should retain control, or perceived control, of the system.

Hou and his colleagues developed an intelligent adaptive system for controlling multiple UAVs and demonstrated that the system significantly reduced operators' workload, improved their situational awareness, and facilitated the operators' ability to work under high time pressure (Hou et al., 2007b). Hou et al. (2007a) also presented a framework, based on their review of more than 200 articles, for designing intelligent adaptive systems. A number of useful guidelines for designing intelligent adaptive systems were provided in this article.

Adaptable systems and adjustable automation are two related schemas for combining automated and manual control. Adaptable systems allow the operator to elicit preprogrammed behaviors during system use similar to the way a coach would send in various "plays" from a playbook during a football game. The advantage of adaptable systems is the introduction of more flexible roles for supervisory control that allow the operator to command complex behaviors without requiring complicated communication protocols (Miller and Parasuraman, 2007). Adjustable automation allows operators to fix the level of system autonomy, allowing them to decide, depending on the changing situation, how much decision authority to reserve for themselves and how much autonomy to delegate (Goodrich, in press; Sellner et al., 2006). The best type of adaptive system depends on the task environment, the amount of complexity required, and the ability of the operator to delegate autonomy during high-workload environments. However, it should be kept in mind that delegation and choosing an appropriate autonomy level can be very high-workload decisions in themselves. Hardin and Goodrich (2009) demonstrated that a mixed-initiative control scheme (i.e., allowing the human operator and the intelligent robotic agents to jointly decide the appropriate level of autonomy) resulted in better overall performance than did adaptive autonomy and adjustable autonomy in a simulated target search task. The authors, however, caution that mixed-initiative control schemes should meet the following requirements in order to be effective:

1. The human operator and the agents should have complementary abilities.
2. Agents should have the capabilities to progress without waiting for commands from the human operator.
3. The human operator must be able to interact with multiple agents efficiently and simultaneously.

The next section further discusses teaming between human and intelligent agents.

6.7 Intelligent Agents and Human-Robot Teaming

The necessity for more powerful intelligent agents that can interact with human operators in increasingly sophisticated ways will require that current performance-improving techniques and technologies be augmented with techniques and technologies that facilitate effective H-A team interactions (Billings, 1996; Bradshaw et al., 2004; Green et al., 2008; Lewis, 1998). In recent years, researchers have designed agents that can support team cognition. Dias et al. (2006), for example, presented the architecture of a dynamically formed human-robot team that performs coordinated tasks. The architecture was developed based on the vision that H-A teams will dynamically form to solve complex tasks by coordinating their complementary capabilities. The architecture included TraderBot (Dias et al., 2004), TeamTalk (Harris et al., 2004), and Plays (Bowling et al., 2004). These components were used to support the development of coordination among both H-A teams and agent-agent teams.

TraderBot supports team coordination by allocating tasks to other agents using a market-based coordination approach. This approach is analogues to and is described within the context of market trading (Dias et al., 2006). Market-based approaches can distribute much of the planning and execution of an operation over the team, gather information about the team, and distribute resources all within a *team aware* context. Within the architecture described by Dias et al., each team member is assigned an interface agent, or *trader* (see Zlot and Stentz, 2006). This agent is the team members' interface to the *market* and simplifies the communication process among human and agent team members. The use of TeamTalk, a multiagent, multimodal dialog system, further simplifies the communication between humans and agents. Finally, the architecture supports shared environment awareness by broadcasting all user input to all robots on the team. Therefore, coordination, communication, and shared awareness are all supported within the architecture.

Yen et al. (2006) presented research on agents that can support the development of shared mental models. These researchers discussed the use of the Collaborative Agents for Simulating Teamwork (CAST) model, which enables agents and humans to anticipate potential information needs and proactively exchange information between team members. Components of the CAST model were tested in a simulated battlefield over two experiments. The ability of CAST to support communication and decision making was investigated. For the scenario used in the first study, the human was considered a virtual agent and invisible to other team agents. Human team members could affect team activities by directly adjusting their agent's behaviors and strategies. For this team, the decision-making process was supported by the interactions (e.g., communication) between the human and the agents; the human provided domain expertise, while the agents gathered relevant information by collaborating with other agents. In experiment one, the use of a CAST-supported communication model (i.e., decision-theoretic) was compared to a non-CAST-supported communication model. Results of the simulation indicated that using the decision-theoretic approach, which analyzes the cost benefit ratio of communicating with other team members vs. not communicating with other team members, produced better decision making than when team members communicated every time.

In the simulated scenario used in the second experiment, humans had an assistant agent that was invisible to the other team members. The assistant agent supported the human by fusing and filtering information received from other agents, tracking the human team member's mental model, and tracking the mental model shared among the team. Here, both the interactions between the human and the agents, and the interaction between the human and the assistant agent supported decision making. For this experiment, the use of information fusion provided by the assistant agent was compared to not using information fusion (i.e., no assistant agent) by assessing the accuracy of decision making, particularly when the human's cognitive capacity was taxed. The results indicated that the simulated fusion team, in general, performed better than the nonfusion team. Furthermore, the disparity in performance between the two simulated teams increased as cognitive capacity decreased.

The results of the two experiments by Yen et al. (2006) suggest that using collaboration models such as CAST to form H-A teams may lead to better performance. However, future research should determine whether the increase in performance was a result of the CAST approach facilitating team cognition. For example, did the decision-theoretic approach support team decision-making processes and/or did fusion lead to an increase in shared mental models among team members? Investigating these questions along with investigating factors that may influence an operator's decision to accept an agent's attempt to establish team cognition (see section 1.2) just begins to open the door to the design of future human-robot team systems.

7. Conclusions

This report examined human performance issues in supervisory control of unmanned vehicles (i.e., robotics) and reviewed user interface solutions that could potentially address those issues. As robotics become increasingly prevalent in both military and civilian operations, it is important to understand HRI and its associated limitations and potentials. In the foreseeable future, it will be more common for humans to work with robots as a team to perform tasks that humans cannot realistically accomplish alone. Research programs, such as the U.S. Army's Safe Operations of Unmanned Systems for Reconnaissance in Complex Environments Army Technology Objective, were also initiated to explore how to enhance operator performance by employing advanced technologies and user interface design concepts. These solutions, and other innovative user interface designs reviewed in this report, can hopefully improve HRI and therefore reduce the current challenges of operators' robotic control tasks.

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List of Symbols, Abbreviations, and Acronyms

AR	augmented reality
AT	activity time
ATC	air traffic control
CAST	Collaborative Agents for Simulating Teamwork
EEG	electroencephalography
EID	ecological interface design
FA	false alarm
FAP	false-alarm prone
FCS	Future Combat System
fMRI	functional magnetic resonance imaging
FO	fan-out
H-A	human-agent
HRI	human-robot interaction
IT	interaction time
LOA	level of automation
MBC	management by consent
MBE	management by exception
MiDAS	Mission Displays for Autonomous Systems
MP	miss prone
SA	situation awareness
UV	unmanned vehicle
UAV	unmanned air vehicle
UGV	unmanned ground vehicle

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