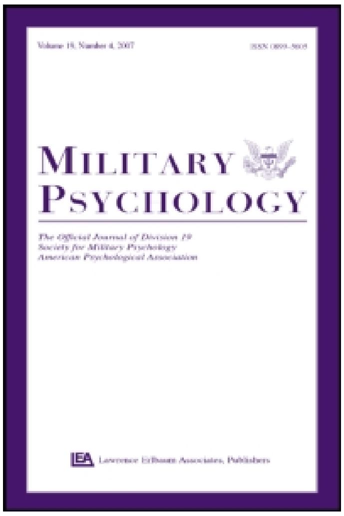

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Adaptive Automation for Human Supervision of Multiple Uninhabited Vehicles: Effects on Change Detection, Situation Awareness, and Mental Workload

Raja Parasuraman [a]; Keryl A. Cosenzo [b]; Ewart De Visser [a]
[a] Arch Lab, George Mason University, Fairfax, Virginia [b] Army Research Laboratory, Human Research and Engineering Directorate, Aberdeen Proving Ground, Maryland

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Raja Parasuraman
Arch Lab, George Mason University, Fairfax, Virginia

Keryl A. Cosenzo
Human Research and Engineering Directorate, Army Research Laboratory, Aberdeen Proving Ground, Maryland

Ewart De Visser
Arch Lab, George Mason University, Fairfax, Virginia

Human operators supervising multiple uninhabited air and ground vehicles (UAVs and UGVs) under high task load must be supported appropriately in context by automation. Two experiments examined the efficacy of such adaptive automation in a simulated high workload reconnaissance mission involving four subtasks: (a) UAV target identification; (b) UGV route planning; (c) communications, with embedded verbal situation awareness probes; and (d) change detection. The results of the first "baseline" experiment established the sensitivity of a change detection procedure to transient and nontransient events in a complex, multi-window, dynamic display. Experiment 1 also set appropriate levels of low and high task load for use in Experiment 2, in which three automation conditions were compared: manual; static automation, in which an automated target recognition (ATR) system was provided for the UAV task; and adaptive automation, in which individual operator change detection performance was assessed in real time and used to invoke the ATR if and only if change de-

Correspondence should be addressed to Raja Parasuraman, Ph.D., Arch Lab, George Mason University, 2055 David King Hall, 4400 University Dr. MS3F5, Fairfax, VA 22030-4444. E-mail: rparasur@gmu.ed

tection accuracy was below a threshold. Change detection accuracy and situation awareness were higher and workload was lower for both automation conditions compared to manual performance. In addition, these beneficial effects on change detection and workload were significantly greater for adaptive compared to static automation. The results point to the efficacy of adaptive automation for supporting the human operator tasked with supervision of multiple uninhabited vehicles under high workload conditions.

INTRODUCTION

Uninhabited vehicles (UVs) and other robotic systems are being introduced in rapid fashion into the military to extend manned capabilities, provide tactical flexibility, and act as "force multipliers" (Barnes, Parasuraman, & Cosenzo, 2006; Cummings & Guerlain, 2007). In the U.S. Army's Future Combat Systems (FCS), for example, battlefield force structures will be redesigned to be flexible, reconfigurable components tailored to specific combat missions. The human operators of these systems will be involved in supervisory control of UVs with the possibility of occasional manual intervention. In the extreme case, soldiers will operate multiple systems while on the move and while under enemy fire. Because of the consequent increase in the cognitive workload demands on the soldier, automation will be needed to support human-system performance. For example, automated decision aids can allow tactical decisions to be made more rapidly, thereby shortening the "sensor-to-shooter" loop in command and control (C^2) systems (Adams, 2001; Rovira, McGarry, & Parasuraman, 2007).

An important design issue is what the level and type of automation should be for effective support of the operator in such systems (Parasuraman, Sheridan, & Wickens, 2000). Unfortunately, automated aids have not always enhanced system performance, primarily due to problems in their use by human operators or to unanticipated interactions with other subsystems. Problems in human-automation interaction have included unbalanced mental workload, reduced situation awareness, decision biases, mistrust, overreliance, and complacency (C. Billings, 1997; Parasuraman & Riley, 1997; Sarter, Woods, & Billings, 1997; Sheridan & Parasuraman, 2006; Wiener, 1988).

Adaptive automation has been proposed as a solution to the problems associated with inflexible automation (Inagaki, 2003; Parasuraman, 2000; Parasuraman & Miller, 2006; Scerbo, 2001). In this approach, information or decision support is not fixed at the design stage but presented appropriately depending on context in the operational environment. Context-sensitive adaptive automation is initiated by the system based on critical mission events, operator performance, or physiological state (Barnes et al., 2006; Parasuraman, Bahri, Deaton, Morrison, & Barnes, 1992). Adaptive systems were proposed over 20 years ago (Hancock, Chignell, & Lowenthal, 1985; Parasuraman et al., 1992; Rouse, 1988), but empirical evaluations of their efficacy have only been conducted over the last decade—in such domains as aviation (Parasuraman, Mouloua, & Hilburn, 1999), air traffic management (Hilburn, Jorna, Byrne, & Parasuraman, 1997; D. B. Kaber & Endsley, 2004), and industrial process control (Moray, Inagaki, & Itoh, 2000). Furthermore, there has been only limited empirical research on adaptive automation to support human supervision of robots or unmanned vehicles (Parasuraman, Galster, Squire, Furukawa, & Miller, 2005; Wilson & Russell, 2007).

The method of invocation in adaptive systems is a key issue (Barnes et al., 2006). Parasuraman et al. (1992) reviewed the major invocation techniques and divided them into five main categories: (a) critical events; (b) operator performance measurement; (c) operator physiological assessment; (d) operator modeling; and (e) hybrid methods that combine one or more of the previous four methods. For example, in an aircraft air defense system, adaptive automation based on critical events would invoke automation only when certain tactical environmental events occur, such as the beginning of a "pop-up" weapon delivery sequence: this would lead to activation of all defensive measures of the aircraft (Barnes & Grossman, 1985). If the critical events do not occur, the automation is not invoked. Hence, this method is inherently flexible and adaptive, because it can be tied to current tactics and doctrine during mission planning. This method requires that the contingencies and critical events are in fact anticipated, which may not always be possible. Another disadvantage of the method is its insensitivity to actual system and human operator performance. One potential way to overcome this limitation is to measure operator performance and/or physiological activity in real time. For example, mental workload may be inferred from performance, physiological, or other measures (Byrne & Parasuraman, 1996; Kramer & Parasuraman, 2007; Wilson & Russell, 2003). The measures can provide inputs to an adaptive system manager (which could be rule or neural network based). The output of this system then invokes automation to support or advise the operator appropriately, with the goal of balancing workload at some optimum, moderate level (Parasuraman et al., 1999; Wilson & Russell, 2003).

In addition to measures of workload, assessment of situation awareness might also be useful in adaptive systems (D. B. Kaber & Endsley, 2004). Reduced situation awareness has been identified as a major contributor to poor performance in search-and-rescue missions with autonomous robots (Burke & Murphy, 2004; Murphy, 2004). In particular, transient or dynamic changes in situation awareness might be captured by probing the operator's awareness of changes in the environment. One such measure is change detection performance. People often fail to notice changes in visual displays when they occur at the same time as various forms of visual transients (Simons & Ambinder, 2005). This "change blindness" phenomenon has typically been demonstrated for basic laboratory tasks or for staged real-world activities such as two-person sporting games or face-to-face social interaction (Simons & Rensink, 2005). Change blindness also occurs with complex visual displays used in various military C^2 environments. Durlach (2004) examined the effect of transient distractor events (i.e., window closing) on detection of changes in icon position, location, and size in a C^2 map display. She showed that changes in icon position on the map (e.g., indicating enemy unit movement) were vulnerable to distractor events; detection performance decreased from 79 to 37% when such distractors were present.

The goal of the present research was to assess the efficacy of adaptive automation on UV operator performance in a simulated reconnaissance mission. Adaptive support was triggered based on the operator's change detection performance. Mission scenarios involved supervision of multiple UVs and required multitasking. Effects of adaptive automation on performance, SA, and workload were examined. We developed an in-house simulation capability, the Robotic NCO, designed to isolate some of the cognitive requirements associated with a single operator controlling robotic assets within a larger military environment (Barnes et al., 2006). The goal was to create a microworld with face validity for future military operations involving UAVs and UGVs while providing for a degree of experimental control. For example, the design of the UGV task (described below) was based on field observations of the Army's Experimental Unmanned Vehicle (XUV) that currently uses an autonomous navigation system in the manner simulated in our studies. The simulation required the participant to complete four interrelated, military-relevant tasks: (s) a UAV target identification task; (b) a UGV route planning task; (c) a communications task with an embedded verbal situation awareness probe task; and (d) an ancillary task designed to assess situation awareness using a probe detection method, a change detection task embedded within a situation map. We conducted two experiments with the Robotic NCO simulation. The first was a "baseline" study, without automation, in which we investigated change detection and other aspects of performance as a function of parametric variation in task load. In a subsequent main experiment, we examined the effects of adaptive automation on performance, workload, and situation awareness in the same task under conditions of low and high task load.

In the baseline experiment we varied task load by manipulating the difficulty of the UAV and communications tasks at each of two levels in a 2 × 2 factorial design. In the embedded change detection task, an icon on the situation map changed its location at unpredictable times during the simulated mission. On the basis of the extensive change blindness literature (Simons & Ambinder, 2005), we predicted that change detection performance would be especially poor if the change occurred when a visual transient was simultaneously present—in this experiment, when the UGV stopped and requested assistance from the operator, in which case the UGV status bar flashed. However, in a complex visual display where many items compete for attention, change detection performance may be poor even without such visual transients, due to the need for attention to be allocated to many different subtasks, windows, and display locations (Durlach, 2004; Parasuraman, Barnes, & Cosenzo, 2007; Thomas & Wickens, 2006). We therefore predicted that change detection accuracy would be low even in the absence of an explicit display transient, although not as low as with the UGV flash event. To test this prediction, we also included change events when participants were engaged in the UAV task, when no explicit visual transient was present.

BASELINE EXPERIMENT

Methods

Participants

Sixteen young adults (9 women, 7 men) aged 18–26 years (mean = 20.5) participated. The experiment lasted approximately 2 hours and participants were paid $15.00 per hour.

Robotic NCO Simulation

The Robotic NCO simulation involved four interrelated tasks that participants had to perform in order to achieve the overall goal of reconnaissance: (a) a UAV target identification task; (b) a UGV route-planning task; (c) a communications task with an embedded verbal situation awareness probe task; and (d) a change detection task. These tasks were presented in separate windows of a computer monitor. At a comfortable viewing distance the display subtended about 44° × 33° of visual angle. In addition, a situation map showing the reconnaissance area was presented in a separate window at the bottom of the display (see Figure 1A). Participants were trained to perform either the UAV or the UGV tasks by switching between the associated display windows using the designated buttons when one task or the other demanded their attention. At the same time, participants were required to respond as needed in the communications, situation awareness probe, and change detection tasks. The simulated mission began with the preplanned flight of the UAV and the movement of the UGV over the terrain to be searched and ended when the UAV had completed its flight, the UGV had completed its route, and the situation map was populated with all identified targets. Total mission time was approximately 5 minutes.

UAV Task. The UAV task simulated the arrival of electronic intelligence hits ("elints") from possible targets in the terrain over which the UAV flew. When a target was detected, it was displayed in the UAV view as a white square in a yellow circle (Figure 1B). Participants were told that when a target was presented, they were to zoom in on that location, which opened up a window of the UAV view

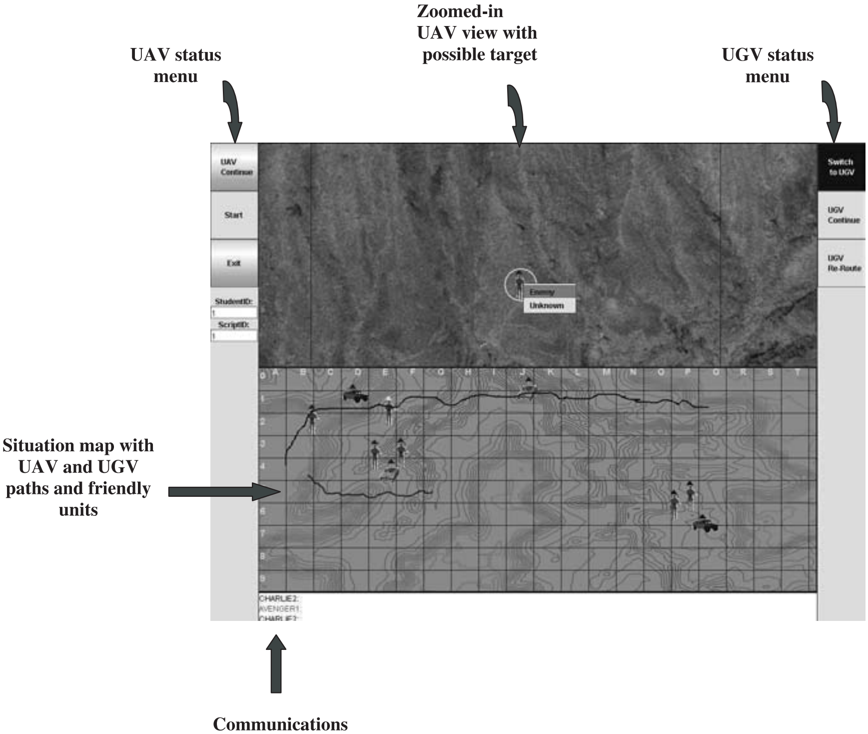

FIGURE 1A Robotic NCO simulation with the UAV task in the zoomed-in view mode. The four subtasks, UAV target identification, UGV route-planning, communications (with embedded verbal situation awareness probes), and change detection (involving unit movement in the situation map), were displayed in separate windows as shown.

(Figure 1A). They were required to identify the target from a list of possible types (for which they had received prior training). The participant clicked the elint marker (i.e., white squares) with the mouse to obtain a clear image of the target. He or she then used a right mouse-click to identify the target as enemy or unknown. An "enemy" was indicated by a red triangle, and an "unknown" was indicated by a yellow triangle. This procedure had to be completed within 6 seconds or the target would disappear, resulting in a "missed" target by the participant. Once identified, the target icon was then displayed on the situation map. The difficulty of the UAV targeting task was manipulated by varying the number of elint targets to be identified, as described below.

UGV Task. At the same time as the UAV continued on its flight path over the terrain, the UGV moved through the area following a series of preplanned waypoints indicating areas of interest (AOI). During the mission, the UGV would stop

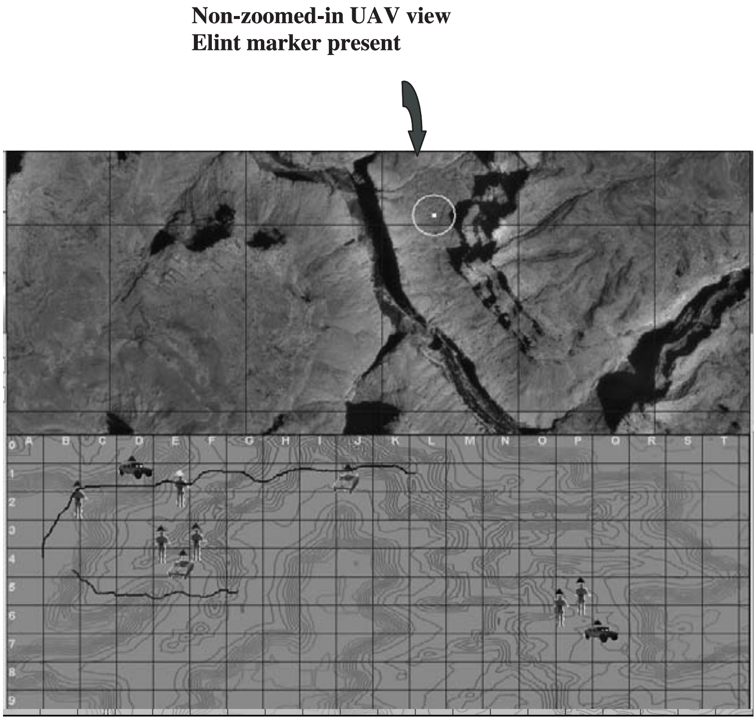

FIGURE 1B The UAV task in the non-zoomed-in view mode and the situation map.

at various times, at which point the UGV status bar would flash. There were two reasons why the UGV stopped: it had reached the named AOI or its path was by blocked by an unknown obstacle. The participant was instructed to then switch to the UGV display and click on the UGV bar that accessed the view (simulating video images) from the UGV (Figure 1C). The UGV did not move forward until the participant selected an action, as follows. If the UGV had reached an AOI, the participant reconnoitered the area and then restarted the UGV along its preplanned path by selecting the Continue button. If an obstacle was present, the UGV view showed a picture of it. (The UGV view was displayed in the same location as the UAV view on the computer monitor.) When the UGV encountered an obstacle, it was one of two types, a blocking obstacle (e.g., log, ditch) or a traversable obstacle. A blocking obstacle required replanning and the participant rerouted the UGV by selecting the Re-route button. A traversable obstacle required that the participant had to resume the UGV along its preplanned path by selecting the Continue button. The difficulty of the UGV monitoring task was kept at a fixed, relatively high level by requiring the participant to respond to a total of seven UGV stops (three AOIs and four obstacles, two blocking and two traversable).

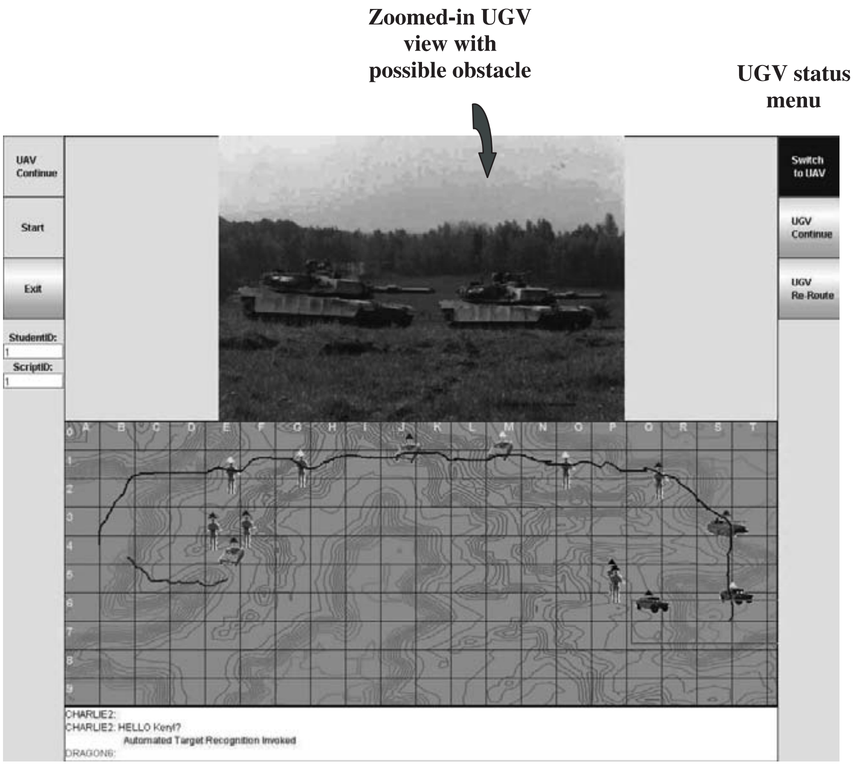

FIGURE 1C The UGV task in zoomed-in view showing possible obstacle.

Communications task 1. Call sign acknowledgment. Participants received messages intermittently while performing the UAV and UGV tasks. Communications were presented both visually in a separate communications window (see Figure 1A) and acoustically over a speaker. The messages requested updates on the UGV/UAV status and the location of particular targets (to assess situation awareness, as described further below). Participants also had to monitor the communications for their own call sign (which they had been given previously). Twenty call sign messages were presented at random intervals and had either to be either acknowledged with a key press if the participant's own call sign was presented or, if different, ignored. Call sign acknowledgement had to occur within 5 seconds of the message or else a missed call sign would result. The difficulty of the communications task was manipulated by varying the proportion of own call signs relative to the total number of call signs presented (see below).

Communications task. 2. Verbal situation awareness probes. The communications task also included embedded messages designed to assess the participants' situation awareness. The questions were presented during the mission and required a "Yes" or "No" response from the participant. The questions spanned Types 1 and 2 of Endsley's (1995) taxonomy of situation awareness—perception and comprehension, respectively. Examples were (a) Has the UGV required rerouting? (b) Are there enemy troops in sector X? (c) Is the UAV in Sector X able to find targets near enemy units? (d) Are there enemy troops within two grid squares of sector X?

These questions were presented without any "freezing" or stoppage of the primary simulated mission. Participants were instructed to respond to the questions when they occurred and then return to performing the other concurrent tasks.

Change detection task. In many tactical military operations, the operator's situation display may often be updated without warning, so that the operator may miss the change. To capture this, a change detection task was embedded into the situation map of the Robotic NCO display to obtain a performance probe-based measure of situation awareness. At unpredictable times during the simulated mission, and after the situation map had been populated to a degree, an icon on the situation map (a target previously identified by the participant) changed its location by two grid squares (~traversing approximately 4° of visual angle). Participants were instructed that such changes might occur and that if they noticed them to press the space bar. Only a simple detection response was required, not identification or recognition. Eight icon changes were presented at random intervals during the 5-minute mission. Half of the changes (four) occurred during one of the UGV stops, when the UGV status bar flashed (transient event condition). The other four changes occurred while participants were engaged in the UAV task (nontransient event condition).

It is important to note that participants were told that the UAV, UGV, and verbal SA communications tasks in this simulation were not independent but coordinated tasks that supported the overall goal—a reconnaissance mission in which participants had to be aware of friendly and enemy unit movements and of the positions of their UAV and UGV assets. The verbal SA queries that were posed over the communications channel provided an evaluation of how well participants followed these instructions. Furthermore, participants were told that they would be asked at the end of the mission to select the best path for a platoon to follow, so that they could not simply ignore UAV targets or enemy units once identified but had to integrate them into their overall map of the battlefield.

Workload and situation awareness questionnaires. A subjective overall rating was given at the end of each 5-minute mission trial on participant's perceived overall workload (OW) and situation awareness. This was a single number from 0 to 100 for each rating. Both OW and situation awareness criteria were adapted from the NASA-TLX (Hart & Staveland, 1998) and the Cognitive Compatibility Situation Awareness Technique questionnaire (CC-SART; Taylor, 1990).

Procedure

Following familiarization, training, and practice on the Robotic NCO simulation, participants performed eight simulated missions, each lasting 5 minutes each. Participants were asked to take the role of a robotic operator in a Mounted Combat System company (MCS). They were asked to conduct a reconnaissance mission for the MCS platoon using their UAV and UGV assets. The UAV and UGV starting point, ending point, and path were preplanned by the experimenter, and except for UGV reroutes, were not under control of the participant. The UAV traveled faster than the UGV and provided surveillance information to the participant as described previously. The UGV followed its routed path and when an event occurred, waited for operator input, as described. While supervising the two robotic assets the operator received communications, either call sign acknowledgments or status queries, and performed the change detection task, as described previously.

The baseline experiment was a 2 × 2 within-subjects design, with the manipulated factors being the difficulty of the UAV and communications (call sign) tasks. For the UAV task, task load or difficulty was manipulated by varying the number of targets. There were 10 targets in the low condition and 20 targets in the high condition. Task difficulty in the communications task was manipulated by varying the uncertainty associated with seeing (hearing) one's own call sign. In the low uncertainty (low difficulty) condition, 16 of the 20 call signs presented were the participant's own call sign; hence, participants had very little uncertainty as to whether their call sign had been presented while engaged in multiple other tasks. In the high uncertainty (high difficulty) condition, only 4 of the 20 call signs were the participant's own. As a result, greater vigilance on the part of the participant was required given the lower probability of own call sign. The two levels of difficulty on the UAV and communications were factorially combined to yield four scenarios, each of which was presented twice, resulting in eight total missions. The order of presentation of mission scenarios was counterbalanced between participants.

The following dependent variables were measured: (a) UAV target acquisition: Accuracy (proportion correct) and RT to identify target as friendly or unknown. (b) UGV route planning: Reaction time (RT) to implement new route on blocking obstacle event or to observe an AOI and continue UGV. (c) Communications: RT and percent missed for own call sign acknowledgments. (d) Change detection: Accuracy (proportion correct) and RT to correctly detected

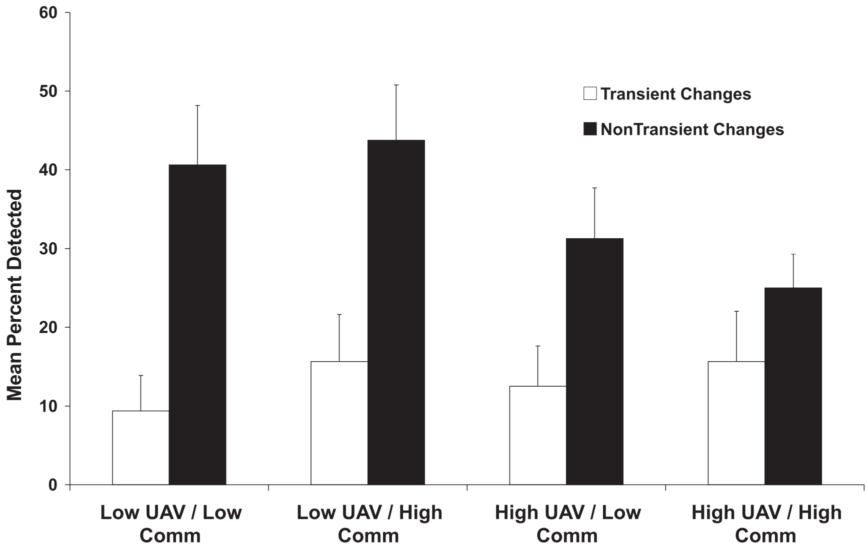

FIGURE 2 Effects of visual transient and nontransient events on change detection accuracy under conditions of low and high UAV and communications task difficulty.

changes. (e) Situation Awareness: Overall situation awareness as measured by the CC-SART, and mean number of correct responses on the situation awareness questions presented in the communications task. (f) Overall workload: OW rating.

RESULTS

Multivariate analyses of variance (MANOVAs) followed by ANOVAs were conducted on the data. The within-subjects variable included in the analyses were communications task difficulty (uncertainty) and UAV task difficulty. For the change detection performance analysis, Change Type was also included as a within-subjects variable.

UAV Target Identification

There was a significant effect of communications task difficulty on UAV target identification performance, F (2,14) = 8.07, $p < .005$. ANOVAs that were run to determine whether RT or accuracy (percentage correct) contributed to the main effect gave a significant effect for RT, F (1,15) = 8.66, $p < .01$. Surprisingly, mean RT to UAV targets was significantly lower when communications uncertainty was high

(x = 1.48 s, SE = .03) than when it was low (x = 1.56 s, SE = .05). There were no other significant effects.

UGV Task Performance

RTs to the UGV stops (continue or reroute) were higher when communications uncertainty was high than when it was low, but this effect was moderated by a significant interaction between UAV task and communications task difficulty, F (1,15) = 5.15, p < .03. Pair-wise comparisons showed that mean RT was lower in the high UAV/low communications uncertainty condition (x = 3.84 s, SE = .36) than in the high UAV/high communications uncertainty condition (x = 5.85 s, SE = .56), p < .001.

Communications Task Performance

There was a significant effect for communications task difficulty on communications task performance, F (1,14) = 158.7, p < .001. ANOVAs showed a significant effect only for RT, F (1,15) = 331.5, p < .01. Mean RT for own call sign acknowledgment was significantly higher when communications task uncertainty was high (x = 3.42 s, SE = .10) than when it was low (x = 2.33 s, SE = .08). There were no other significant effects.

Change Detection Performance

Overall, change detection accuracy (Figure 2) was relatively poor but was nevertheless affected by the presence (UGV task) or absence (UAV task) of visual transients (Change Type). There was a significant effect of Change Type, F (1,15) = 13.9, p < .02. Fewer changes were detected when there were visual transients (x = 13.3%, SE = 4.40) compared to when transients were not present (x = 35.2%, SE = 4.20). There was also a significant interaction between Change Type and UAV task difficulty, F (1,15) = 10.2, p < .001: for transient events, there was no effect of UAV Task difficulty, possibly because accuracy was near floor (~13%); for nontransient events, however, change detection accuracy was significantly lower under high (28.1%) than under low (42.2%) UAV task difficulty, F (1,15) = 6.16, p < .02.

Analyses of change detection RT showed no significant effects of communications task and UAV task difficulty or of Change Type.

Verbal Situation Awareness Probes

There were no significant effects of level of difficulty for the UAV or communications tasks on the number of situation awareness questions answered correctly. The mean number correct (out of 4), irrespective of condition, was 2.67 (SE = .11)

Situation Awareness and Workload

Results for overall situation awareness showed a significant main effect for the levels of situation awareness, $F(2,14) = 5.98$, $p < .01$, as measured by the CC-SART. Paired comparisons of the data showed that the score for level of processing ($x = 3.68$, SE = .36) was significantly lower than ease of reasoning ($x = 5.68$, SE = .31) and activation of knowledge ($x = 5.43$, SE = .30), $p < .001$. Ease of reasoning and activation of knowledge did not differ significantly.

Results for overall workload showed a significant main effect for the levels of workload, $F(5,11) = 17.81$, $p < .001$. Paired comparisons of the data showed that mental demand was significantly higher than all the other levels except for effort, *p*s < .05. Further, physical demand was significantly lower than all the other levels except for frustration, *p*s < .01. Frustration was also significantly lower than all the other levels, *p*s < .01. No other comparisons were significant.

DISCUSSION

The baseline experiment was designed to assess performance levels on the Robotic NCO simulation in response to variation in task load. The goal was to determine an appropriate overall task difficulty level that could be used to assess effects of adaptive automation in a subsequent main experiment. The baseline study was also run to determine whether change detection performance could be sensitively assessed in the context of a complex multitask simulation. With respect to the first goal, the study was successful: appropriate conditions of task loading were identified. However, the results showed that some task load manipulations had the expected effect on performance, whereas others did not. For example, high uncertainty on the communication task led to longer RTs for own call sign acknowledgment, as predicted. However, unexpectedly the same task difficulty manipulation led to lower RTs on the UAV target identification task, for unknown reasons. The effects of UAV and communications task difficulty on performance on the UGV route-planning task were also generally as expected, with longer RTs to reroute the UGVs under the more difficult conditions. Overall, therefore, the results indicate that a high number of UAV targets and greater uncertainty in the communications task would provide a sufficiently challenging level of task difficulty for use in the main experiment.

With respect to the second goal of the baseline experiment, assessment of change detection performance, the results were encouraging. Change detection accuracy was typically low, ranging from 9.4 to 43.8% across the various conditions This result indicates that the change blindness effect, which has typically been demonstrated in simple laboratory tasks or contrived social interactions (Simons & Ambinder, 2005; but see Durlach, 2004), also occurs with more realistic displays relevant to real-world environments. Given that change detection reflects a perceptual component of situation awareness, the low values suggest a major potential source of system inefficiency in multi-UV operations. Despite the low overall level, however, change detection performance was, as predicted, poorer for changes occurring during transient events (UGV task) than during nontransient events (UAV task). This indicates that the change detection procedure we used was sensitive and is encouraging with respect to the potential for using it to assess when adaptive automation might be useful to support the human operator supervising multiple UVs. Another index of the sensitivity of the change detection task is that accuracy during nontransient events (UAV task) was reduced when the UAV task difficulty was increased from low to high, suggesting that the increased attentional demand associated with more UAV targets was reflected in poorer awareness of changes in the situation map.

MAIN EXPERIMENT

In the main study we examined the effects of adaptive automation, based on real-time assessment of operator change detection performance, on performance, situation awareness, and workload in supervising multiple UVs in the Robotic NCO simulation under two levels of task load. We used an adaptive automation invocation method first developed by Parasuraman, Mouloua, and Molloy (1996), known as *performance-based* adaptation. In this method, individual operator performance (i.e., change detection performance) is assessed in real time and used as a basis to invoke automation. In contrast, in static or model-based automation, automation is invoked at a particular point in time during the mission based on the model prediction that operator performance is likely to be poor at that time (Parasuraman et al., 1992). This method is by definition not sensitive to within- or between-individual differences in performance, because it assumes that all operators are characterized by the model predictions. In performance-based adaptive automation, on the other hand, automation is invoked if and only if the performance of an individual operator is below a specified threshold at a particular point in time during the mission. If a particular operator does not meet the threshold at that time, automation is invoked. However, if the threshold is exceeded in another operator, or in the same operator at a different point in the mission, the automation is not invoked. Thus, performance-based adaptation is by definition context-sensitive to an extent.

To demonstrate the potential benefit of adaptive automation, it must be compared not only to performance without automation (manual performance) but to static automation (Barnes et al., 2006; Parasuraman, 1993). Accordingly, in the main experiment, we examined performance in the Robotic NCO task under three conditions: (a) manual; (b) static automation, in which participants were supported in the UAV task with an automated target recognition (ATR) system that detected and identified targets; (c) adaptive automation, in which the ATR automation was invoked if change detection performance was below a threshold, but not otherwise. Each of these conditions was combined factorially with two levels of task load, as manipulated by variation in the difficulty of the communications task.

We predicted that change detection performance and situation awareness as assessed using the verbal situation awareness probes would both be enhanced with adaptive automation, whereas overall mental workload would be reduced, following the logic of Parasuraman et al. (1996, 1999). In turn these benefits would be greater for the adaptive compared to the static automation condition, with both automation conditions being superior to manual performance. Finally, we expected that the selective benefits of adaptive automation, if found, would be greater under high task load than under low task load.

METHODS

Participants

Sixteen young adults (8 women, 8 men) aged 18–28 years (mean = 21.9) participated. The experiment lasted approximately 2 hours and participants were paid $15.00 per hour.

Procedure

Participants performed the same Robotic NCO simulation used in the baseline experiment. There was a fixed, high number of UGV requests (7) and a fixed, high number of UAV targets (20). These task parameters were combined with either a low (16 own call signs in 20) or high level of uncertainty (4 own call signs in 20) in the communications task to create two conditions of overall task load, low and high. In addition, the change detection procedure of the baseline experiment was used. Based on the results of the baseline experiment, this combination of task difficulty variables was considered to represent the most challenging performance conditions and therefore the most suitable for potential mitigation through adaptive automation.

The procedure was the same as the baseline experiment with one exception. At the beginning of the experiment, participants were told that an automated target recognition system might be invoked during the missions. They were also given training on the ATR prior to the main experimental blocks. When the automation was about to be invoked, the participant received a message (presented both auditorially through the speaker and visually in the communications window), indicating that the ATR was now available. Note that the ATR automated the function of target identification, but participants still had to attend to the results of the automation. Participants could not simply ignore the UAV task when ATR was provided because they needed to integrate the information provided by its sensor to support the overall goal of reconnaissance. As described in the Methods section previously, they were also given SA queries, some of which asked about the relative position of the UAV or of identified enemy units. Participants were also instructed to monitor the results of the ATR. Finally, they were required at the end of the mission to evaluate the best platoon path to take following the reconnaissance mission. Hence, the ATR automation did not simply remove a task but supported the overall mission goal.

There were three main automation conditions. In the Manual condition, participants performed all four tasks of the Robotic NCO simulation without automated support. In the Static Automation conditions participants were supported in the UAV task with an ATR system, thereby off-loading them of the responsibility of identifying targets but not of the responsibility of using the UAV sensor information or monitoring its path and evaluating its position with respect to friendly and enemy units. The automation was invoked in the middle (at ~2.5 min) of the 5-minute mission (after four change detection events) in all participants and irrespective of the level of performance. A similar procedure was used in the Adaptive Automation condition, except that the Robotic NCO software maintained a running count of an individual operator's change detection accuracy. After four change detection events had occurred in the middle (at ~2.5 minutes) of the 5-minute mission, the current count of detection accuracy was compared to a threshold. If the threshold was not met, the ATR automation was invoked, but not otherwise. Based on the results of the baseline experiment as well as pilot work, a threshold of 50% accuracy was chosen. It was expected with this threshold that many participants would receive adaptive aiding, with the proportion being higher under high than low task load. After adaptive automation invocation (or not), the mission continued as before; that is, the ATR remained on until the end of the block.

The three automation conditions (Manual, Static, Adaptive) were combined factorially with task load (low or high) for six mission scenarios (each lasting 5 minutes). Each of these conditions was repeated (blocks) in order to see whether any adaptive automation effects would be reduced with additional practice. The experiment was therefore a 2 × 3 × 2 within-subjects design. The within-subjects factors were the uncertainty of the communications task (low or high), automation condition (Manual, Static, and Adaptive Automation), and block (one and two).

Each participant completed twelve 5-minute mission blocks. The order of blocks was counterbalanced. For statistical evaluation of the effects of automation, mission phase (pre-automation invocation and post-automation invocation—in the middle of the 5-minute mission) was included as a factor. For comparability, even though automation was not invoked in the manual condition, performance measures were calculated for each mission phase in this condition as well.

The same dependent variables as in the baseline experiment were used, with the exception that the CC-SART was dropped and only the verbal situation awareness probes were used. Of the four verbal situation awareness questions, two were given in each half of every mission. Because of the low number of questions in each half, only an overall verbal situation awareness accuracy score was computed.

RESULTS

Because the main hypotheses that were tested in this study involved the change detection measure, we report the results for this dependent variable first, followed by performance on the UAV, UGV, and communications tasks and the subjective ratings.

MANOVAs and ANOVAs were conducted for the data. The within-subjects variables included in the statistical analyses were communications task difficulty, mission phase (pre-post automation), automation condition, and block. Because there were no significant interactions involving the block factor, the data were collapsed across this factor.

Change Detection Performance

The adaptive ATR was not invoked in three participants in the low task load/adaptive automation condition when it was first performed (block 1). The ATR was also not invoked in one participant in the second block of this condition. In the high task load/adaptive automation condition, the ATR was invoked in all participants. The results of the statistical analyses were the same whether these participants were included or excluded in the data set. Therefore, we first present results with the data from all the participants, irrespective of whether the ATR was invoked adaptively for them in the adaptive automation condition.

Results for the change detection accuracy scores revealed significant main effects for automation condition, F (2, 30) = 22.8, $p < .001$; mission phase, F (1, 15) = 151.3, $p <. 001$; and communications task difficulty, F (1, 15) = 37.5, $p < .001$. In addition, the interaction of mission phase and automation condition was significant, F (2,30) = 22.1, $p < .001$. To examine the interaction further, separate ANOVAs were computed for both the pre-automation invocation and post-invocation phases. In the pre-invocation phase before automation was implemented, there were no significant differences in change detection accuracy between conditions. However, the effect of automation condition was significant for the post-invocation phase, F (2,30) = 31.3, $p <. .001$. As shown in Figure 3, and as verified by pair-wise comparisons, participants detected significantly more icon changes in the situation map in the static and adaptive automation conditions compared to the manual condition, ps < .001. Furthermore, change detection accuracy was signifi-

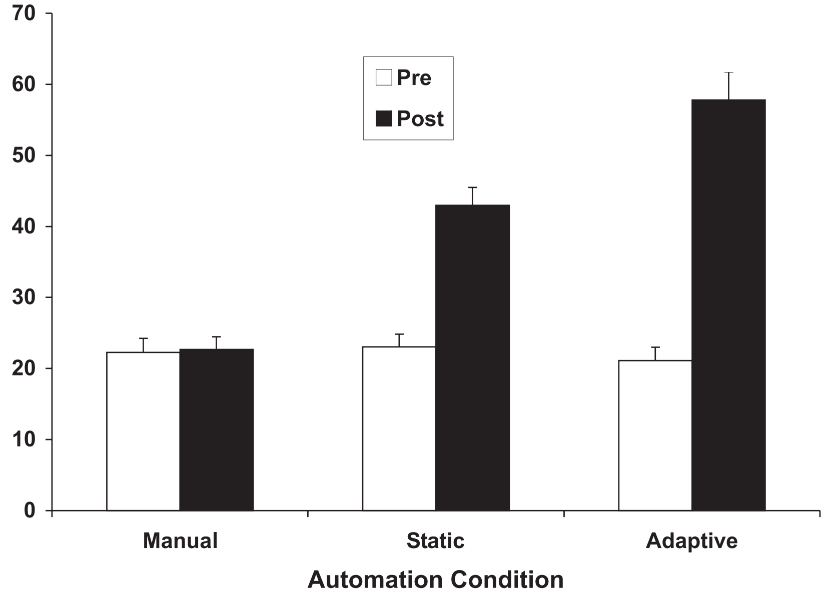

FIGURE 3 Effects of static and adaptive automation on change detection accuracy, compared to manual performance. Values are shown for the pre-automation invocation (Pre) and post-automation invocation (Post) mission phases.

cantly higher in the adaptive automation condition than in the static automation condition, $p < .02$. Finally, more changes were detected when the uncertainty of the communications was low ($x = 36.0\%$, SE = 1.22) than high ($x = 27.2\%$, SE = .94). However, although we predicted a greater effect of adaptive automation on change detection accuracy under high than low task load, the Automation Condition × Communications Task difficulty interaction, F (2, 30) = 1.06, and the Automation Condition × Mission Phase × Communications Task difficulty interaction, F (2, 30) = 2.24, were not significant.

Overall, there was a marked improvement in change detection accuracy with automation, from a mean of 22.6% in the manual condition to a mean of 50.3% in the two automation conditions, a 112% improvement. More importantly, there was a 54% improvement in change detection performance specifically associated with adaptive automation, from an accuracy of 42.9% in the static condition to 57.8% in the adaptive condition.

We also compared change detection performance in those participants for whom automation was not invoked adaptively with those in whom it was. Recall that the ATR was not invoked adaptively in three participants in the low task load condition because they exceeded the threshold (see Figure 4), whereas it was in 13

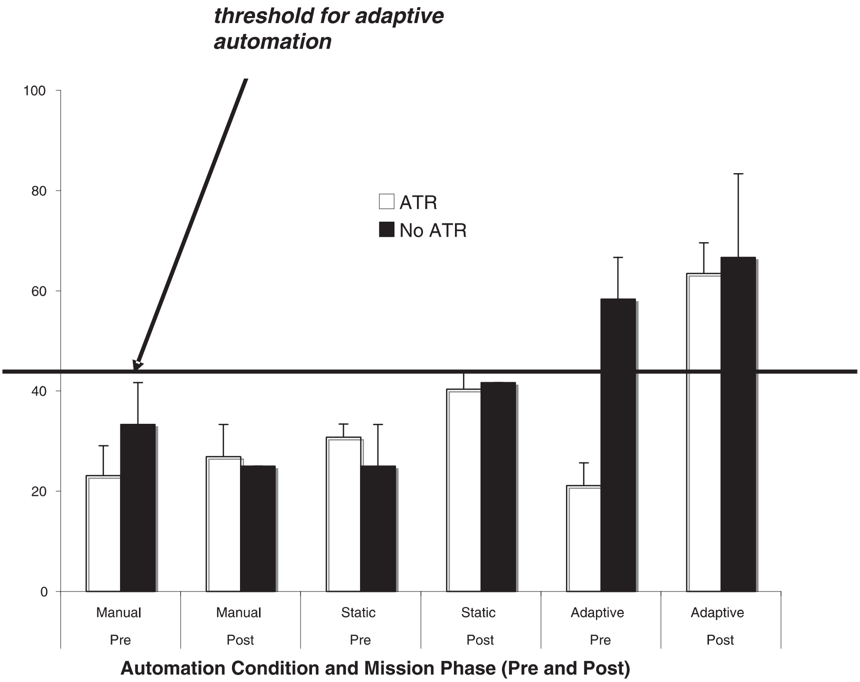

FIGURE 4 Change detection accuracy in participants for whom automation was not invoked adaptively (No ATR) and in those for whom it was triggered (ATR), for pre- and post-invocation periods. The mean performance levels of the same participants (No ATR and ATR) in the manual and static automation conditions are also shown.

others. Figure 4 shows the change detection performance of these two groups in the pre- and post-invocation mission phases. By definition, the non-ATR group had superior change detection accuracy to the ATR group in the pre-invocation phase, as confirmed by a *t*-test adjusted using Levene's test for unequal variances (due to unequal group sample sizes), $t = 4.26$, $p < .05$. In the post-invocation phase, however, the two groups did not differ significantly, $t = .1$, $p > .8$. Thus, adaptive automation had the effect of "bringing up" the performance of the 13 participants to the level of the three for whom adaptation was not required at that point in the mission. Figure 4 also shows the mean performance levels of the same non-ATR and ATR participants in the manual and static automation conditions. This shows the same pattern of results as in Figure 3 where participants were not subgrouped in this manner: both static and adaptive automation led to superior performance compared to manual performance, with the adaptive automation condition leading to a further improvement.

UAV Target Identification

Performance on the UAV target identification task was analyzed only for the first half of each mission phase, because this function was automated in the second half. There were no significant differences in target identification accuracy or RT between the manual, static automation, or adaptive automation conditions. There was also no significant effect of communications task difficulty on UAV target identification performance in the pre-invocation phase.

UGV Route Planning

There were no significant effects or interactions of automation condition or mission phase on performance of the UGV route planning task. There was a significant main effect for communications task difficulty, F (1, 15) = 9.57, $p < .007$. Results showed that RTs to the UGV stops (continue or reroute) were higher when communications uncertainty was high (x = 4.39 s, SE = 0.14) than low (x = 4.26 s, SE = 0.42).

Communications Task

The main effects of automation condition, F (4,12) = 10.5, $p < .001$; phase, F (2,14) = 32.4, $p < .001$; and communications task difficulty, F (2,14) = 83.7, $p <$ .001, were significant for communications performance (accuracy and RT). In addition the Automation Condition × Phase interaction was significant, F (4,12) = 16.3, $p < .001$. All other interactions and main effects were significant, ps < .01. To determine whether RT or percentage correct contributed to the significant interactions and main effects, ANOVAs were run. Results revealed that percentage correct and RT contributed significantly to the main effect of communications task difficulty, F (1,15) = 51.8, $p < .000$ and F (1,15) = 70.39, $p < .001$, respectively. A greater percentage of call signs were responded to and with greater speed (i.e., lower RT) in the low uncertainty communications condition (correct: x = 86.9%, SE = 1.29; RT: x = 1.29 s, SE = .01) than the high uncertainty communications condition (correct: x = 65.3%, SE = 1.67; RT: x = 1.29 s, SE = .02).

ANOVAs also showed a significant interaction of automation condition and phase for percent of call signs acknowledged, F (2,30) = 7.07, $p < .003$. The interaction indicates that though there was no significant difference between conditions in the pre-invocation phase, $F < 1.0$, there was a significant difference in the post-invocation phase F (2,30) = 20.9, $p < .001$. As Figure 5 shows, and as pair-wise comparisons confirmed, more call signs were responded to correctly in the static and adaptive automation conditions than in the manual condition, ps < .003. Furthermore, more call signs were responded to in the adaptive condition than the static condition, p <. 008.

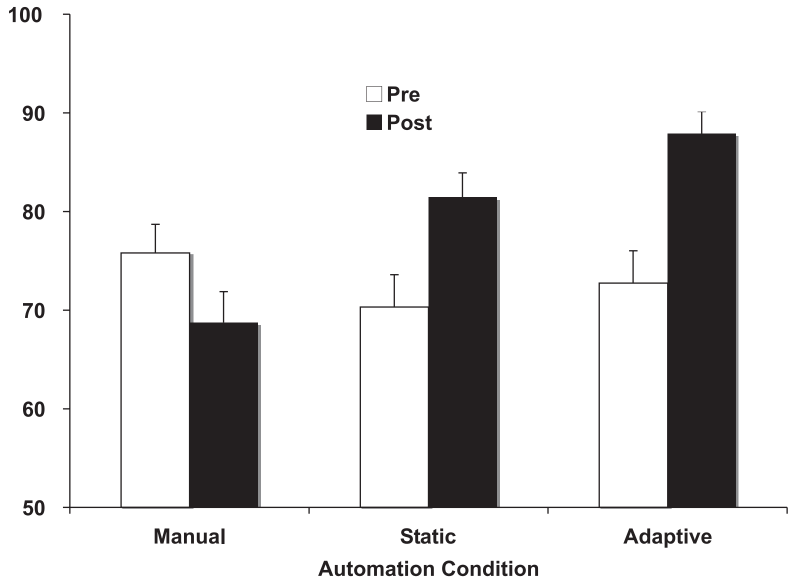

FIGURE 5 Effects of static and adaptive automation on communications task accuracy, compared to manual performance, for pre- and post-invocation periods.

ANOVAs showed a significant interaction of automation condition and phase difficulty for RT to call signs, F (2,30) = 19.55, $p < .001$. RT did not differ between conditions in the pre-invocation phase, $F < 1.0$, but did in the post-invocation phase, F (2,30) = 23.1, $p < .001$. Call signs were responded to more quickly (i.e., lower RTs) in the adaptive condition (x = 1.27 s, SE = .04) than the static (x = 1.48 s, SE = .02) or manual (x = 1.51 s, SE = .02) condition, ps < .001. There was no significant difference for RTs between the manual and static automation conditions.

Situational Awareness Probes

There were significant main effects of phase, F (1,15) = 18.1, $p = .001$, and automation condition, F (2,30) = 12.87, $p < .001$, and a significant interaction of automation condition and phase, F (2,30) = 9.95, $p = .001$ for the percentage of situation awareness questions correctly answered. To examine the interaction further, ANOVAs were conducted for each level of phase. There was no significant difference in answer accuracy between conditions prior to automation invocation. There was a significant difference between automation conditions after automation invocation, F (2,30) = 19.9, $p < .001$. Pair-wise comparisons showed that showed that more situation awareness questions were answered correctly in the static (x =

58.2%, SE = 5.06) and adaptive automation (x = 65.62, SE = 4.03) conditions than in the manual condition (x = 29.7%, SE = 4.08), ps < .001 (see Figure 6). The difference between the adaptive and static automation condition was not significant.

Overall Workload

There was a significant main effect for automation condition for subjective ratings of overall workload, F (2,30) = 23.5, p < .001. No other main effects or interactions were significant. Reported workload was lowest in the adaptive automation condition (x = 23.8, SE = 1.07), intermediate in the static automation condition (x = 32.5, SE = 2.28), and highest in the manual condition (x = 42.5, SE = 2.78), with all pair-wise comparisons significant, ps < .001.

Relationships Between Change Detection, Situation Awareness, and Workload

The interrelationships between change detection, situation awareness, and workload are shown in Figure 7, which plots mean values for these measures in the post-invocation phase as a function of automation condition. Automation, and

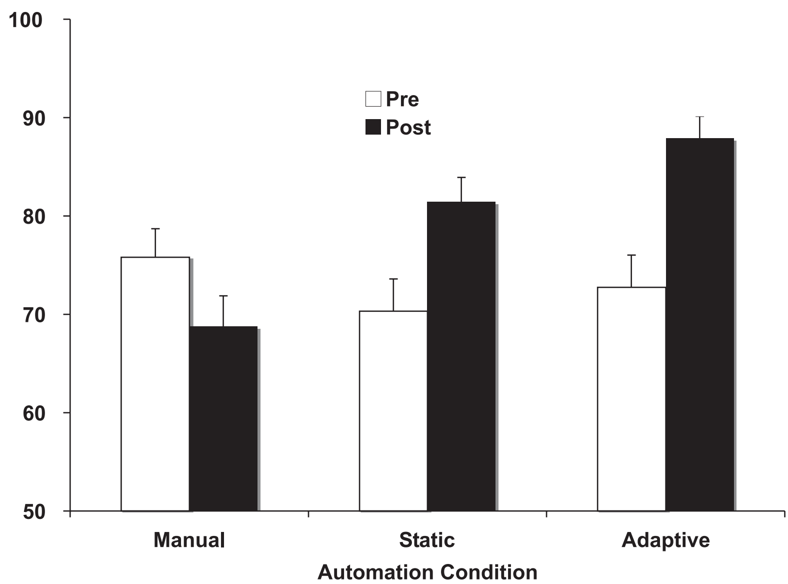

FIGURE 6 Effects of static and automation on accuracy of verbal situation awareness probes, compared to manual performance, for pre- and post-invocation periods.

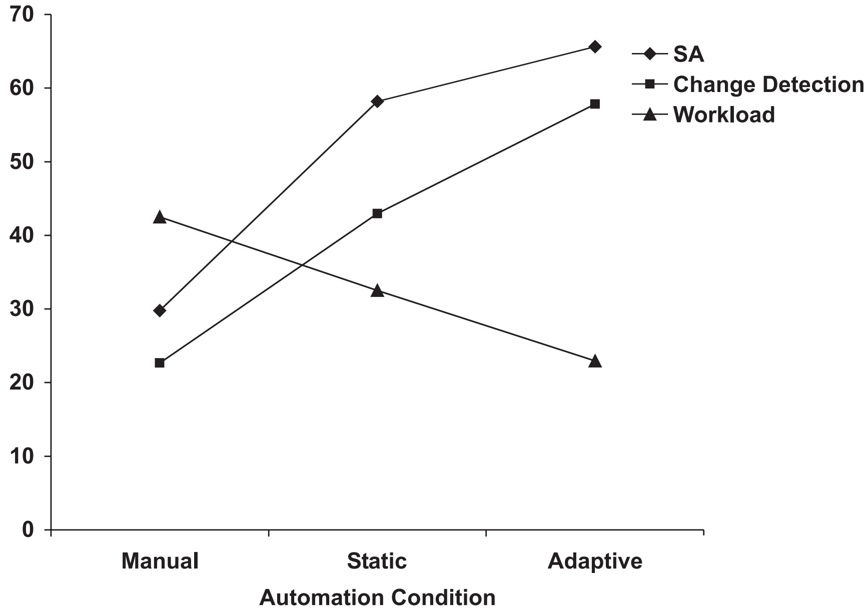

FIGURE 7 Interrelationships between effects of static and adaptive automation on change detection, situation awareness, and workload. The change detection and situation awareness measures are indexed by percentage correct, whereas workload was indexed by a subjective rating from 1 to 100.

adaptive automation specifically, increased change detection accuracy and reduced subjective workload, as indicated by the reciprocal relationship between these measures illustrated in Figure 7. In addition, automation also enhanced situation awareness, but though the mean situation awareness scores were greater for adaptive compared to static automation, these values were not statistically different.

DISCUSSION

High cognitive workload demands on personnel in military systems working with multiple UVs has mandated the use of automation support (Barnes et al., 2006). Because automation does not always achieve the goal of supporting the operator effectively (C. Billings, 1997; Parasuraman & Riley, 1997; Sarter et al., 1997), providing context-appropriate aiding—adaptive automation—has been proposed (Miller & Parasuraman, 2007; Parasuraman et al., 1992; Scerbo, 2001). In the present study, adaptive aiding was provided to participants supervising multiple UVs, based on real-time assessment of their change detection accuracy. We compared the effects of manual performance, static automation, and adaptive automation on workload, situation awareness, and other aspects of task performance.

We predicted that change detection performance and situation awareness would be enhanced with adaptive automation, whereas overall mental workload would be reduced, and that these benefits would be specifically associated with adaptive (as opposed to static) automation. The results supported this prediction. Compared to manual performance, both static and adaptive automation led to an increase in change detection accuracy and situation awareness, whereas workload was reduced. In addition, in comparison to static automation, there was a further increase in change detection accuracy and concomitant reduction in workload with adaptive automation. This last finding is important, because simply demonstrating performance benefits due to automation is insufficient; rather, the specific benefit, if any, of adaptive automation must be shown, over and above that associated with static automation (Barnes et al., 2006; Parasuraman, 1993). The results thus add to the growing literature pointing to the efficacy of adaptive automation for reducing or balancing operator workload and enhancing performance (Inagaki, 2003; D. Kaber & Riley, 1999; Parasuraman et al., 1999; Scerbo, 2001) and confirm that these benefits also accrue in the domain of human operator supervision of multiple UVs in a simulated tactical reconnaissance mission.

There was a reciprocal relationship between the different operator performance measures in terms of the effects of adaptive automation. Specifically, static automation led to an increase in both change detection accuracy and situation awareness and a decrease in workload, with a further increase and decrease in these measures with adaptive automation (see Figure 7). However, it should be noted that the additional increase in situation awareness with adaptive automation was not statistically significant. Several studies have documented benefits of adaptive automation for situation awareness (D. B. Kaber & Endsley, 2004). It is possible that the nonsignificant trend we found might simply reflect the relative insensitivity of our verbal probe measure, because we provided only two such probes in the post-invocation phase of each mission during which automatic target recognition was implemented. Nonetheless, the substantial benefits for change detection and overall workload—a 34% enhancement in the case of the former—argue strongly for the efficacy of adaptive automation. The reduction in overall workload was also reflected in better performance of one of the other three subtasks that participants performed, the communications task. Accuracy in responding to communications was higher with static automation than with manual performance, and higher still with adaptive automation. Thus adaptive automation was successful not only in supporting the human operator in an appropriate context—when their change detection performance was low, pointing to low perceptual awareness of the evolving mission elements—but also freed up sufficient attentional resources to benefit performance on other less critical but important subtasks.

The specific advantage that adaptive automation based on assessment of individual performance or physiology brings is its sensitivity to within- and between-individual differences, whereas other approaches such as model-based adaptive automation are not (Parasuraman et al., 1992). This benefit was apparent when we compared the participants for whom automation was not invoked adaptively in the low task load condition to those for which automation was triggered. We found that though change detection performance was initially higher in the former group (the criterion for not invoking automation), both groups had equivalent levels of change detection accuracy in the post-invocation mission phase. Thus, in comparison to static automation, adaptive automation, by providing aid only in certain individuals when they need it, or in the same individual when he or she needs it at different times, has the effect of "leveling" performance between and within individuals, thus providing for more stable system performance.

What are the practical implications of the research reported in this article? This work is part of a broader Army science and technology program aimed at understanding the performance requirements for human-robot interaction in future battlefields (Barnes et al., 2006). Initial findings from this project indicate that the primary tasks that soldiers are required to perform place severe limits on their ability to monitor and supervise even a single UV, let alone multiple UVs. For example, Chen, Durlach, Sloan, and Bowens (2008) examined target detection accuracy in participants given either a single robotic asset (either a UAV, a UGV, or a teleoperated UGV) or all three assets. Target detection performance was lower with three than with a single UV, and participants were also less likely to complete their missions in the allotted time. In addition, crew safety may be compromised because soldiers who have to carry out routine tasks such as radio communications and ensuring local security also have to supervise and manage several robotic tasks during high workload mission segments (Chen & Joyner, 2009; Mitchell & Henthorn, 2005). Adaptive automation would therefore be particularly well suited to these situations because of the uneven workload and the requirement to maintain SA for the primary as well as the robotic tasks. Our results point to the efficacy of adaptive automation for supporting the human operator under these conditions.

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