

Adaptable and Adaptive Automation for Supervisory Control of Multiple Autonomous Vehicles

Brian Kidwell,¹ Gloria L. Calhoun,² Heath A. Ruff,³ Raja Parasuraman¹

¹George Mason University, ²Air Force Research Laboratory

³Ball Aerospace & Technologies Corporation

Supervisory control of multiple autonomous vehicles raises many issues concerning the balance of system autonomy with human interaction for optimal operator situation awareness and system performance. An unmanned vehicle simulation designed to manipulate the application of automation was used to evaluate participants' performance on image analysis tasks under two automation control schemes: adaptable (level of automation directly manipulated by participant throughout trials) and adaptive (level of automation adapted as a function of participants' performance on four types of tasks). The results showed that while adaptable automation increased workload, it also improved change detection, as well as operator confidence in task-related decision-making.

INTRODUCTION

Effective supervisory control of multiple autonomous systems requires an efficient control scheme that balances system autonomy with human interaction. This necessitates assistance to the operator, without displacing the operator from the central role of overseeing operation of all vehicles. Traditionally, static automation has often been used as a means to alleviate operator workload and improve overall capabilities. Parasuraman, Sheridan, and Wickens (2000) define automation as "a device or system that accomplishes (partially or fully) a function that was previously, or conceivably could be, carried out (partially or fully) by a human operator" (p. 287). Inherent to the use of static automation, however, are issues of reduced mode and situational awareness, complacency, mistrust, and skill degradation, all part of the larger user out-of-the-loop problem (Endsley & Kiris, 1995; Parasuraman & Riley, 1997).

A growing body of literature suggests the problems of static automation may be mitigated by the implementation of a system of adaptive automation. Adaptive automation has been theorized to alleviate some of the drawbacks attributable to static automation, including subjective feelings of "automation surprise," mode awareness, situational awareness, as well as to contribute overall improved task performance (Cosenzo, Parasuraman, Novak, & Barnes, 2006; Kaber & Endsley, 2003). Adaptable automation (Opperman, 1994) may mitigate many of the same ill-effects of automation (Miller & Parasuraman, 2007). Adaptive and adaptable automation differ according to whether the machine or the operator, respectively, possesses ultimate responsibility for controlling the level of automation. As suggested by Miller and Parasuraman (2007), there exists a tradeoff between control and workload on the continuum of adaptive and adaptable automation (Figure 1). In this tradeoff, adaptive automation represents a shift toward decreased workload with a likely accompaniment of decreased user involvement, as a result of decreased responsibility in maintaining system control. Adaptable automation represents the opposite effect. As the user's responsibility for system supervision is augmented with the role of delegating levels of automation, there is an increased cognitive demand, albeit with the benefit of yielding

automation that is more predictable to the user and at a higher level of system specificity.

The benefits of adaptive automation are well documented (Cosenzo et al., 2006; Kaber & Endsley, 2003; Calhoun, Ward, & Ruff, 2011), as are the effects of adaptable automation, albeit to a lesser extent (Miller, Funk, Goldman, Meisner, & Wu, 2005; Parasuraman, Galster, Squire, Furukawa, & Miller, 2005; Squire & Parasuraman, 2010). Few empirical studies, however, have been conducted to directly compare the effects of the two types of automation on human and system performance.

This study addresses overall task performance as it relates to delegation responsibility in a flexible automation system. Specifically, two control schemes were compared: adaptable automation and adaptive automation. Adaptable automation may be useful insofar as it allows a user to specifically tailor the level of automation (LOA) to suit current and/or future workload. Additionally, this may assist in modifying the automated support in accordance with individual differences, better fitting the system according to personality, working memory capacity, or spatial ability (De Visser, Shaw, Mohamed-Ameen, & Parasuraman, 2010; Chen & Barnes, 2012). The act of delegation itself may also serve to reduce a user's tendency to be complacent and instead promote attention towards monitoring system status and task completion. However, the steps for a user to change LOAs may negatively contribute to workload and mental demand. In contrast, an adaptive scheme that automatically rebalances workload as the need arises might be more effective for optimal human-system performance.

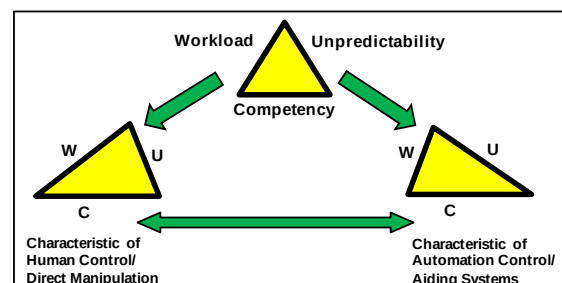


Figure 1. Tradeoff in adaptable and adaptive control. Adapted with permission from Miller and Parasuraman (2007).

Report Documentation Page				Form Approved OMB No. 0704-0188	
Public reporting burden for the collection of information is estimated to average 1 hour per response, including the time for reviewing instructions, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing the collection of information. Send comments regarding this burden estimate or any other aspect of this collection of information, including suggestions for reducing this burden, to Washington Headquarters Services, Directorate for Information Operations and Reports, 1215 Jefferson Davis Highway, Suite 1204, Arlington VA 22202-4302. Respondents should be aware that notwithstanding any other provision of law, no person shall be subject to a penalty for failing to comply with a collection of information if it does not display a currently valid OMB control number.					
1. REPORT DATE 12 OCT 2012		2. REPORT TYPE		3. DATES COVERED 00-00-2012 to 00-00-2012	
4. TITLE AND SUBTITLE Adaptable and Adaptive Automation for Supervisory Control of Multiple Autonomous Vehicles				5a. CONTRACT NUMBER	
				5b. GRANT NUMBER	
				5c. PROGRAM ELEMENT NUMBER	
6. AUTHOR(S)				5d. PROJECT NUMBER	
				5e. TASK NUMBER	
				5f. WORK UNIT NUMBER	
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) Air Force Research Laboratory, Wright-Patterson Air Force Base, OH, 45433				8. PERFORMING ORGANIZATION REPORT NUMBER	
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 unlimited					
13. SUPPLEMENTARY NOTES To be presented at the HUMAN FACTORS and ERGONOMICS SOCIETY 56th ANNUAL MEETING, Boston, MA October 22-26, 2012					
14. ABSTRACT Supervisory control of multiple autonomous vehicles raises many issues concerning the balance of system autonomy with human interaction for optimal operator situation awareness and system performance. An unmanned vehicle simulation designed to manipulate the application of automation was used to evaluate participants' performance on image analysis tasks under two automation control schemes: adaptable (level of automation directly manipulated by participant throughout trials) and adaptive (level of automation adapted as a function of participants' performance on four types of tasks). The results showed that while adaptable automation increased workload, it also improved change detection, as well as operator confidence in task-related decision-making.					
15. SUBJECT TERMS					
16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT Same as Report (SAR)	18. NUMBER OF PAGES 6	19a. NAME OF RESPONSIBLE PERSON
a. REPORT unclassified	b. ABSTRACT unclassified	c. THIS PAGE unclassified			

METHOD

Experimental Design

Twelve voluntary participants (5 male, 7 female), ranging from age 19 to 26 (mean=22.5) were monetarily compensated for participating in the study. All signed consent forms allowing use of their data. Participants all self-reported having 20/20 vision or correctable vision, as well as normal color vision. None had prior piloting experience or knowledge of the experiment and testbed software.

A single factor, within subject design, was employed. Trials were blocked according to automation type, three 15-min trials within each block. The order of the blocks (automation type) was counterbalanced across participants.

Simulation Testbed

The ALOA (Adaptive Levels of Autonomy, Version 3) research testbed developed by OR Concepts Applied (ORCA; Johnson, Leen, & Goldberg, 2007) was used. This testbed incorporates the ORCA commercially available routing software/mission planner to provide needed complexity and realism. The testbed consisted of a Dell Precision Workstation T7500 computer (64 bit operating system, 12 gigabytes of RAM, a Nvidia Quadro FX4800 graphics card, dual Intel Xeon 2.66 MHz quad-core processors) and dual 24-in widescreen monitors (resolution 1920 x 1200; 59 Hz).

Experimental Tasks

The tasks incorporated into the experiment were meant to represent the cognitive demands envisioned for supervising multiple autonomous vehicles. Experimental tasks included: detection of the appearance of a map symbol representing a hostile aircraft (change detection), allocation of targets requiring imaging to vehicles, routing of vehicles to accomplish imaging, and analysis of images. Participants were instructed to prioritize the tasks, in the order just described,

with detecting hostile aircraft the top priority and shedding the secondary image analysis task if workload became unmanageable, as well as other secondary tasks (retrieving information from the chat and timeline displays and detecting changes in systems status). Figure 2 provides an illustration of the formats with labels showing the primary windows utilized to accomplish each task. There were approximately 6-7 task events every minute of each 15-min trial. More details on each task type (as well as any randomization constraints) are available in a description of a different experiment using the same testbed (Calhoun, Ruff, Draper, & Wright, 2011).

Some of the task types (change detection, system status, and information retrieval) required monitoring displays and making inputs in response to information displayed. Other tasks (allocation of new imaging tasks to the vehicles, re-routing the vehicles, and image analysis) employed intermediate LOAs that involved both the operator and the automation system for completion. For the allocation and re-routing tasks, the LOA remained constant at one intermediate level during the trials. However, for the image analysis task, three different intermediate LOAs were employed.

LOAs of Image Analysis Task

As the vehicles automatically progressed along their navigational routes of flight, 30 targets (depicted as dark blue triangles in Figure 2) yielded an image that the participant analyzed. The prompt for an Image Analysis Task was the appearance of a bar in the image analysis window that included the vehicle identifier and time remaining for analysis. Participants had 20 seconds to complete the analysis before the image disappeared and was recorded as a “miss.” Task completion began with bar selection which called up a top-down photo overlaid with 19-26 basic geometric shapes (diamonds, squares, circles, and triangles). Analysis of the image consisted of counting the number of diamonds. This shape counting task was used to minimize participant training requirements and yet represent the cognitive demands of analyzing images in operational applications.

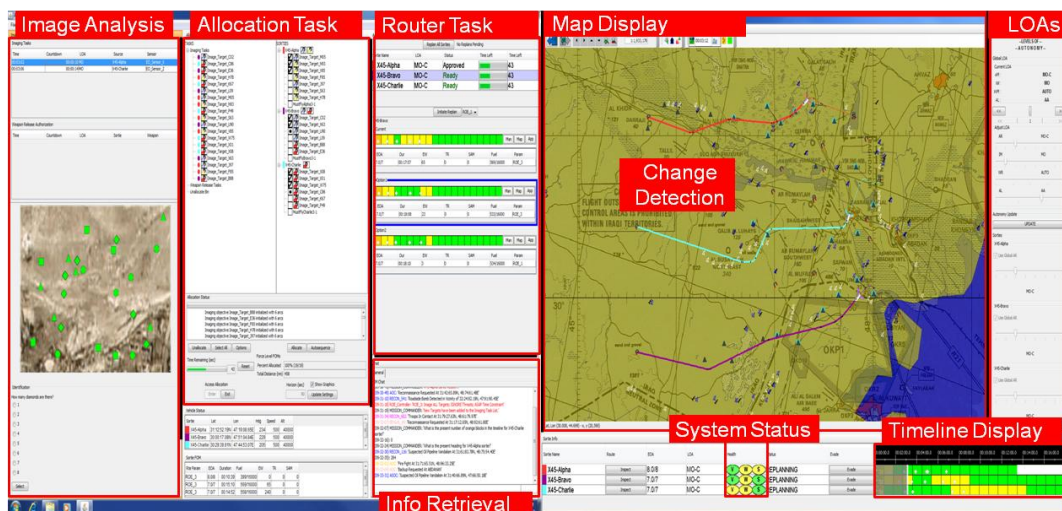


Figure 2. Multiple vehicle supervisory control ALOA testbed showing windows used for tasks.

Three different intermediate LOAs were employed for the image analysis task. In the *low* intermediate level, the automation presented eight options below the image, each with a different number (see Figure 2). Participants were tasked with selecting the option that corresponded to the number of diamonds in the image (1, 2, ... 8). To complete the task and clear the photo, participants clicked "Select." In a *medium* level, the automation highlighted its recommended option to assist image analysis and reduce cognitive workload. All options were selectable. If the participant agreed with the automation's recommendation, only the "Select" button needed to be clicked. However, a different value, followed by the "Select" button could be clicked. At a third *high* LOA, the automation presented only its recommended option and the automation acted on this option, unless the participant vetoed the action within 20 seconds. The reliability of the automation was 90%, similar to that employed by Levinthal and Wickens (2006) and Moray, Inagaki, and Itoh (2000).

Automation Control Schemes Evaluated

Adaptable Automation. Trials started out with the image analysis task in the *low* LOA. With adaptable control, the participant could change the LOA at any time during the trial, and as frequently as desired. To change the LOA to any of the three described above, participants adjusted a movable marker on the LOA tab (rightmost window, Figure 2).

Adaptive Automation. Trials with adaptive automation also began with the *low* LOA. If the participant's workload remained within experimenter specified thresholds, the LOA stayed at this level. However, if performance exceeded the thresholds, indicating the participant was over loaded, the LOA increased to the *medium* LOA. If the participant's performance indicated that the participant was over loaded with the *medium* LOA the LOA increased to *high*.

Increasing LOA in response to high cognitive/workload demands was only one part of the adaptive cycle. The LOAs also decreased to re-engage the operator in the task load, if the performance measures, in respect to the thresholds, indicated that workload had returned to being manageable.

Thresholds for Performance-based Adaptive Automation

Performance on four different task types (see Table 1) determined when the LOA was changed in the adaptive automation condition. For each task, two thresholds were established, each specifying a time length in seconds.

Table 1.

Thresholds for Level of Automation (LOA) Changes

Participants' Task	Performance Threshold		Frequency Per Trial
	To Lower LOA (-1)	To Increase LOA (+1)	
Allocation	5 s	8 s	5
Image Analysis	5 s	8 s	30
Change Detection	5 s	8 s	4
System Status	5 s	8 s	30

Each time a task type listed in Table 1 was completed, its recorded completion time was immediately compared to both thresholds. If the measure was less than the lower threshold (e.g., < 5 s for allocation task) a '-1' was logged; if greater than the higher threshold (> 8 s), a '+1' was logged. If the time was within the defined thresholds for that task, a '0' was logged. A running count of the logged values was maintained throughout the trial and whenever the sum equaled ± 4 , the LOA changed. If the sum was +4, the LOA increased (from low to medium or medium to high). The LOA dropped (high to medium or medium to low) if the sum equaled -4. For two states, the ± 4 value did not result in an LOA change: -4 if LOA was already at low and +4 if LOA already at high. Each time the LOA changed, the running count was reset to zero. (The threshold and adaptive algorithm were determined from pilot studies to be sensitive to workload and induce LOA changes in this task environment.) Participants were informed that the "LOA may change as a result of performance to assist your workload throughout the trial LOA." A scale depicted the current LOA in the rightmost window (Figure 2).

Procedures

Participants first read and completed an informed consent form and answered a few demographic questions. Next, they completed a personality inventory using the 40 Mini-Marker Personality Scale (Saucier, 2003).

Training began with an explanation of the testbed's displays and controls. Participants were briefed on the scenarios and were informed that the vehicles flew automatically along their flight paths. The automation was described as "reliable, but not perfect." Next, each task type was described and practiced, in turn, in a single task environment, using the automation condition assigned for the first trial block. This was followed by a series of training trials, gradually increasing the number of task types included in each trial. Training continued until accuracy and response times stabilized in trials that matched the task loading of experimental trials.

This portion of training took approximately 120 min to complete and was followed by three 15-min experimental trials with the assigned automation condition. After each trial, participants completed experimenter developed Likert-type rating scales addressing task difficulty, trust in automation, perceived task performance, situation awareness, workload level, adequacy of automation feedback, and impact of automation on performance. Similar procedures were used for the automation condition assigned for the second trial block.

The entire session time, including training and questionnaire completion, was approximately 4 hr per participant.

RESULTS

LOA Changes and Automation Control Schemes

Participants made a mean of 2.24 changes of LOA in the adaptable condition. A mean of 3.36 changes were invoked in the adaptive condition. In both conditions, the ratio between

increases and decreases in LOA was approximately 3:1. In adaptable trials, all 12 participants changed the LOA at least once during the trials. In the adaptive condition, all 12 participants experienced an LOA shift at least once throughout the trials, with 9 of 12 reporting that they felt the frequency with which the LOA changed was sufficient.

The mean time spent in each LOA as a function of automation control scheme is shown in Figure 3 (error bars are standard error of the mean in this and other data plots). The time spent in each LOA varied significantly by automation type ($F(2,22) = 4.299, p < .05$). Post-hoc multiple comparisons indicated that participants spent significantly more time in the *low* LOA in the adaptive condition than in the adaptable condition ($p = .01$). Participants spent significantly more time in the *medium* LOA in the adaptable condition than in the adaptive condition ($p < .05$). In post-trial feedback, 7 of 12 participants indicated that given the choice, they preferred the *medium* LOA. The results also suggested that the extraversion personality factor was a determinant of LOA choice in the adaptable control scheme. Increased levels of extraversion correlated with selection of the *high* LOA ($r = .789, p < .01$), as well as the disuse of the *medium* LOA ($r = -.823, p < .01$). There was not a significant relationship between extraversion and the *low* LOA. The other personality measures did not significantly vary with participants' selection of LOA.

Participants' questionnaire ratings indicated that the adaptable automation increased participant confidence in decision-making ability for the image task more than the adaptive automation ($F(1,11) = 13.200, p < .01$). Additionally, ratings were more favorable for adaptable automation in general, with 8 out of 12 of participants indicating that they preferred it to adaptive automation, and 7 out of 12 indicating they preferred it for the image analysis task.

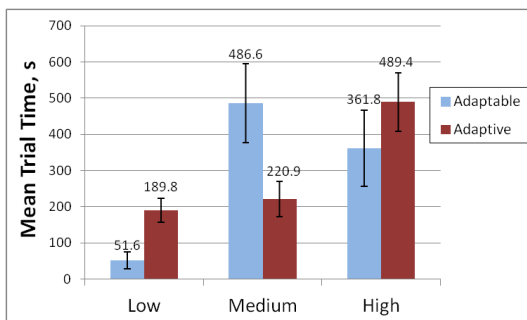


Figure 3. Mean time spent in each level of automation as a function of automation control scheme.

Task Performance with Adaptable and Adaptive Automation

Image Analysis Task. Paired comparisons of all participants indicated no significant differences between control schemes in all performance measures. However, removing data for participants who only made a single LOA change in the trial during the first 5 s yielded a valuable subgroup for investigation. In all, 6 participants were removed for lack of manipulation of automated capabilities. In order to maximize the effect of a limited sample size, pairwise deletion, one-way ANOVAs were used to analyze collected

data. The results indicated that the mean time to complete the image analysis task showed marginally significant differences as a function of automation condition ($F(1,16) = 4.067, p = .06$). Mean image task completion time was slightly slower with adaptable automation (< 1 s) compared to that with adaptive automation (Figure 4). Image analysis accuracy was 90% in both conditions (not statistically different, $p = .815$).

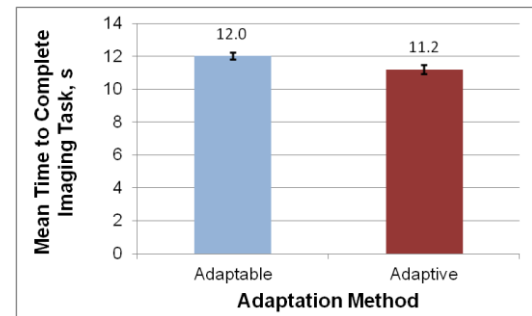


Figure 4. Mean image analysis task time for adaptable and adaptive automation control conditions.

Other Tasks. The image analysis task was the only task in which the LOA could change as a function of the adaptable or adaptive control schemes. Performance on other tasks, however, may have also benefitted from attentional resources freed up with image analysis automation. In fact, a pairwise deletion, one-way ANOVA of the change detection task showed an advantage for adaptable automation (Figure 5): mean change detection rate was higher (100%) with adaptable automation compared to that with adaptive automation (91.7%; $F(1,14) = 5.250, p < .05$). Mean response time for this task was higher in the adaptable (7.3 s) compared to the adaptive conditions (6.0 seconds), but this difference was not significant ($p = .353$).

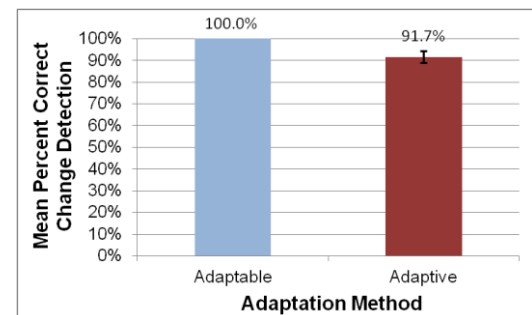


Figure 5. Mean change detection rate for adaptable and adaptive conditions.

DISCUSSION

Adaptive and adaptable automation have been proposed as an alternative to traditional automation to mitigate automation bias and complacency, reduce workload, and improve situational awareness. Key distinctions remain to be made parsing the unique effects of both adaptive and adaptable automation. The present research suggests that adaptable automation augments change detection, in comparison to performance with a performance-based adaptive control scheme. The act of delegating LOAs itself

may serve to better keep the operator in-the-loop and alert to unexpected stimuli. While change blindness may be mitigated by an adaptive automation system (Parasuraman, Barnes, & Cosenzo, 2007; Parasuraman, Cosenzo, & de Visser, 2009), there may be additional benefit to more directly involving the operator in decision processes that force attention to error-prone systems. Adaptable automation serves this function, focusing the operator on system operations.

The cognitive overhead of delegating LOAs in any adaptable system is inherently larger than that of a system in which the operator is removed from the decision-making process. This heightened demand on attentional resources has been noted elsewhere (Kirlik, 1993) for increasing workload beyond that imposed by the task itself. This increase in workload is theorized in Figure 1 and represents the cost of reducing unpredictability in an automated system. Alternatively, adaptable automation may have facilitated a speed-accuracy tradeoff in which participants conceded current task performance for improved performance across all task demands. Another factor to consider is that the results reflect the benefits of manipulating LOAs to change the control between the operator and the system, rather than the control scheme in effect.

Certain personality characteristics may influence automation use. Automation use may be moderated by the extraversion of the user: highly extraverted participants chose the highest LOA which only required a response if they wanted to veto the automation's recommendation. In contrast, less extraverted participants chose a LOA that required a consent response. Interestingly, measures of agreeableness and conscientious were unrelated with automation usage. More research is warranted in order to better understand how personality may affect reliance on automation.

Future work remains for the study of control schemes enabling human supervision of multiple autonomous vehicles. In the present experiment, only the LOA of one task, the image analysis task, was manipulated in the adaption control schemes. A simulation environment with multiple automated tasks within the overall task setting needs to be evaluated for effective LOA interactions and enhanced supervisory control of multiple autonomous vehicles. Of particular concern is whether mode awareness problems are induced as noted by Di Nocera, Lorenz, and Parasuraman (2005) and Calhoun, Ruff, et al. (2011). Personality measures may also relate to other aspects of performance with automated systems, in addition to LOA selection in an adaptable control scheme.

ACKNOWLEDGEMENTS

This research was supported in part by an appointment to the Student Research Participation Program at the U.S. Air Force Research Laboratory (AFRL). The related funding was administered by the Oak Ridge Institute for Science and Education through an interagency agreement between the U.S. Department of Energy and AFRL. Brian Kidwell and Raja Parasuraman were supported by Air Force Office of Scientific Research grant FA9550-10-1-0385 and the Center of Excellence in Neuroergonomics, Technology, and Cognition (CENTEC).

REFERENCES

- Calhoun, G.L., Ruff, H.A., Draper, M.H., & Wright, E.J. (2011). Automation level transference effects in simulated multiple unmanned aerial vehicle control. *Journal of Cognitive Engineering & Decision Making*, 5(1), 55-82.
- Calhoun, G.L., Ward, V.B.R., & Ruff, H.A. (2011). Performance-based adaptive automation for supervisory control. In *Proceedings of the Human Factors & Ergonomics Society*, pp. 2059-2063.
- Chen, J.Y.C., & Barnes, M.J. (2012). Supervisory control of multiple robots: Effects of imperfect automation and individual differences. *Human Factors*, 54(2), 157-174.
- Cosenzo, K., Parasuraman, R., Novak, A., & Barnes, M. Army Research Laboratory, Human Research and Engineering Directorate. (2006). *Implementation of automation for control of robotic systems* (ARL-TR-3808).
- De Visser, E., Shaw, T., Mohamed-Ameen, A., & Parasuraman, R. (2010). Modeling human-automation team performance in networked systems: Individual differences in working memory count. *Proceedings of the Human Factors and Ergonomics Society*, San Francisco, pp 1087-1091
- Di Nocera, F., Lorenz, B., & Parasuraman, R. (2005). Consequences of shifting from one level of automation to another: main effects and their stability. In D. de Waard, K.A. Brookhuis, R. van Egmond, & T. Boersema (Eds.), *Human Factors in Design, Safety, and Management* (pp. 363-376). Maastricht, the Netherlands: Shaker Publishing.
- Endsley, M., & Kiris, E. (1995). The out-of-the-loop performance problem and level of control in automation. *Human Factors*, 37(2), 381-394.
- Johnson, R., Leen, M., & Goldberg, D. (2007). Testing adaptive levels of automation (ALOA) for UAV supervisory control (Technical Report AFRL-HE-WP-TR-2007-0068), Air Force Research Laboratory.
- Kaber, D.B., & Endsley, M.R. (2003). The effects of level of automation and adaptive automation on human performance, situation awareness and workload in a dynamic control task. *Theoretical Issues in Ergonomics Science*, 1-40.
- Kirlik, A. (1993). Modeling strategic behavior in human-automation interaction: Why an "aid" can (and should) go unused. *Human Factors*, 35(2), 221-242.
- Levinthal, B. R., & Wickens, C. D. (2006). Management of multiple UAVs with imperfect automation. In *Proceedings of the Human Factors and Ergonomics Society*, pp. 1941-1944.
- Miller, C.A., Funk, H., Goldman, R., Meisner, J., & Wu, P. (2005). Implications of adaptive vs. adaptable UIs on decision making: Why "automated adaptiveness" is not always the right answer. *Proceedings of the 1st International Conference on Augmented Cognition*, Las Vegas.
- Miller, C.A., & Parasuraman, R. (2007). Designing for flexible interaction between humans and automation: Delegation interfaces for supervisory control. *Human Factors*, 49(1), 57-75.
- Moray, N., Inagaki, T., & Itoh, M. (2000). Adaptive automation, trust, and self-confidence in fault management of time-critical tasks. *Journal of Experimental Psychology: Applied*, 6(1), 44-58.
- Opperman, R. (1994). *Adaptive user support*. Hillsdale, NJ: Erlbaum.
- Parasuraman, R., Barnes, M., & Cosenzo, K. (2007). Adaptive automation for human-robot teaming in future command and control systems. *The International C2 Journal*, 1(2), 43-68.
- Parasuraman, R., Cosenzo, K.A., & de Visser, E. (2009). Adaptive automation for human supervision of multiple uninhabited vehicles: Effects on change detection, situation awareness, and mental workload. *Military Psychology*, 21(2), 270-2.
- Parasuraman, R., Galster, S., Squire, P., Furukawa, H., & Miller, C. (2005). A flexible delegation interface enhances system performance in human supervision of multiple autonomous robots: Empirical studies with RoboFlag. *IEEE Transactions on Systems, Man, and Cybernetics. Part A: Systems and Humans*, 35, 481-493.
- Parasuraman, R., & Riley, V. (1997). Humans and automation: Use, misuse, disabuse, abuse. *Human Factors*, 39(2), 230-253.
- Parasuraman, R., Sheridan, T., & Wickens, C. (2000). A model for types and levels of human interaction with automation. *IEEE Transactions on Systems, Man, and Cybernetics*, 30(3), 286-297.
- Saucier, G. (2003). Orthogonal markers for orthogonal factors: The case of the Big Five. *Journal of Research in Personality*, 36, 1-31.
- Squire, P. N., & Parasuraman, R. (2010). Effects of automation and task load on task switching during human supervision of multiple semiautonomous robots in a dynamic environment. *Ergonomics*, 53(8), 951-961.