Mission Control of Multiple Unmanned Aerial Vehicles: A Workload Analysis

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With unmanned aerial vehicles (UAVs), 36 licensed pilots flew both single-UAV and dual-UAV simulated military missions. Pilots were required to navigate each UAV through a series of mission legs in one of the following three conditions: a baseline condition, an auditory autoalert condition, and an autopilot condition. Pilots were responsible for (a) mission completion, (b) target search, and (c) systems monitoring. Results revealed that both the autoalert and the autopilot automation improved overall performance by reducing task interference and alleviating workload. The autoalert system benefited performance both in the automated task and mission completion task, whereas the autopilot system benefited performance in the automated task, the mission completion task, and the target search task. Practical implications for the study include the suggestion that reliable automation can help alleviate task interference and reduce workload, thereby allowing pilots to better handle concurrent tasks during single- and multiple-UAV flight control.

INTRODUCTION

Unmanned aerial vehicles (UAVs) provide many benefits over manned systems, including having smaller platforms, being more cost efficient, enabling longer mission times, allowing flight control that may not be possible with manned aircraft (e.g., higher g forces and deeper enemy penetration), and avoiding loss of human life. UAVs allow for a variety of civilian and military missions not previously available with manned aircraft (Gawron, 1998) and allow these missions to be flown without endangering the pilots, who remain at remote control stations (Mouloua, Gilson, & Hancock, 2003).

Currently the U.S. Army flies two of its UAVs, the Hunter and Shadow (short- to medium-range tactical reconnaissance UAVs), with two operators for each vehicle. In order to increase the number of UAVs flying without increasing personnel requirements, there is interest in having a single pilot fly one UAV or even two UAVs concurrently. Given the multitasking nature of UAV missions, the concern is that achieving these goals could create serious workload problems.

In order to establish the feasibility of this goal, two approaches – pilot-in-the-loop simulation and computational modeling – should be taken in parallel. The first approach is to evaluate ways of reducing unacceptable workload levels that a 1:1 and, in particular, a 1:2 operator-to-aircraft ratio will impose on the single operator. In our UAV simulation, crafted from interviews with subject-matter experts (U.S. Army UAV pilots attached to E Company, 305th Military Intelligence Battalion), the control of each of two UAV workstations involves three major visually distributed subtasks: (a) mission completion, which involves navigating the UAV between command targets and reporting information at those locations; (b) monitoring the health of various on-board system parameters in order to detect and respond to periodic system failures; and (c) surveillance of the ground beneath each path through a 3-D camera image to find well-camouflaged "targets of opportunity" (TOOs) and then identify them through demanding image manipulation (Gugerty & Brooks, 2001). In a sense, Task a is the primary mission task, Task b supports the mission completion, and Task c can

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be represented as a valuable secondary task that increases the productivity of a UAV mission. In our simulation, two of these tasks are augmented by automation: an autopilot can handle all aspects of navigating the UAV (but provides no benefit to the command target report portion of this task), and an autoalert system can replace visual monitoring with auditory detection of system failures.

The second approach is to develop a computational model of multitask-processing assumptions about the pilot-UAV system in order to predict how these and other workload-relevant modifications to the system might influence pilot workload (Laughery & Corker, 1997; Walters, Huber, French, & Barnes, 2002). Doing so can greatly reduce the time and expense of pilot-in-the-loop simulations. If the model is validated, then questions can be answered more rapidly regarding workload implications of automation and pilot-vehicle ratio modifications of the type described. The current article focuses primarily on the first approach.

A review of the literature indicates that although many human factors issues – display design, crew coordination, time delays, and so forth – have been noted in the UAV paradigm (e.g., Gawron, 1998; Mouloua et al., 2003), few of these issues have been resolved through experimental control. Previous UAV research has focused primarily on single-UAV operation (e.g., Gugerty & Brooks, 2001; Veltman & Oving, 2003), primarily via part-task simulations with few, if any, attempts to generalize to multiple-UAV operation. Other research has focused on controlling multiple robotic objects such as missiles (e.g., Cummings & Guerlain, 2003); however, these types of robotics are fairly simple to operate and make fewer demands on resources than do complex UAV systems. Some generalization to the UAV workload paradigm might be made via air traffic control studies (e.g., Lamoureux, 1999). These studies describe a supervisory task of multiple objects; however, this domain generally does not attempt to optimize resource allocation or deal with combat stresses and consequences (Cummings & Guerlain, 2003). A small number of studies have dealt with supervisory control of multiple systems on a single display (e.g., Moray & Rotenberg, 1989), with the conclusion that operators tend to deal with one complex task at a time and that this approach generally fails to optimize parallel performance. When dealing with multiple complex systems on separate displays, even a moderate number of displays produced response time penalties, which were evident at relatively low levels of complexity (Murray & Caldwell, 1996).

Finally, only one study that we know of has evaluated automation issues with multiple UAVs, with the conclusion that automation management by consent (automation proposes action and waits for operator's consent before taking action) was more beneficial to performance than management by exception (automation acts immediately unless operator specifically cancels action) or manual control (Ruff, Narayanan, & Draper, 2002).

The purpose of the current experiment was to address three issues as pilots performed three tasks with single- and dual-UAV simulations: (a) What would be the extent of workload overload, which we operationally define here as concurrent task interference when pilots fly one and also two UAVs? (b) How would the workload overload of single- and dual-UAV control be buffered by harnessing the two forms of automation (that which accomplishes the navigation task [autopilot] and that which supports mission functioning [system failure monitoring])? (c) What would be the implications of these data for computational models of multitask performance and workload overload (Dixon, Wickens, & Chang, 2003; Sarno & Wickens, 1995)?

METHOD

Participants

Thirty-four male and 2 female licensed pilots (ages 18–25 years) from the Institute of Aviation at the University of Illinois participated in the experiment. Participants were remunerated for their time at a rate of \$8/hr, plus bonuses of \$10 and \$5 for first- or second-place finishes, respectively, out of groups of 6 pilots.

Apparatus

The simulation ran on an Evans and Sutherland SimFusion 4000q with dual 1.0-GHz processors. An OPENsim graphics card generated each of the UAV displays on separate Hitachi

CM721F 19-inch (48-cm) monitors, using 1280 × 1024 resolution. Figure 1 presents a sample display for a single UAV.

As shown in Figure 1, each UAV display was subdivided into four separate windows for each main task. At the top left, a 3-D egocentric display allowed pilots to view the terrain directly below the UAV. During loitering patterns, pilots had access to both *x* and *y* axis panning as well as a 100× zoom feature, used to inspect targets. At the bottom left, a 2-D top-down navigational display portrayed the entire 32- × 32-km simulated world, with coordinates along each axis. At the bottom center, the message box presented flight instructions (fly-to coordinates and report question) for 15 s at a time. These instructions were the only way that pilots could determine the correct flight path. A "repeat key" was available if pilots forgot the flight instructions at any time during the flight. A sample report question might have been "How many tanks are there and where are they located in relation to the building?" In the autoalert condition, these instructions were presented by synthetic voice only. In the autopilot condition, the pilots could also enter fly-to coordinates in a space at the lower half of this box. At the bottom right, four system gauges representing various system parameters allowed pilots to monitor and diagnose the "health" of the UAV. Each gauge had a white bar that oscillated continuously and unpredictably, driven by sine waves ranging in bandwidth from 0.01 to 0.025 Hz. A white bar moving into a red zone indicated a system failure (SF).

Pilots were seated approximately 0.5 m from the UAV display. In the single-UAV flight control, one display monitor was located directly in front of the pilot, and in the dual-UAV flight control, two monitors were located side by side in front of the pilot. In the dual-UAV flight control, each mission operated independently of the other, with separate airspaces, flight paths, and targets. A Logitech digital 3-D joystick was used for navigation, with additional buttons for target detection, loitering, zoom, and SF detection, and an X-Key 20-button keypad was provided for reporting locations of SFs and entering fly-to coordinates. Separate joysticks and keypads were provided for each UAV.

Conditions

The experiment contained three interface conditions: baseline (mostly manual navigation), autoalert, and autopilot. During the baseline and

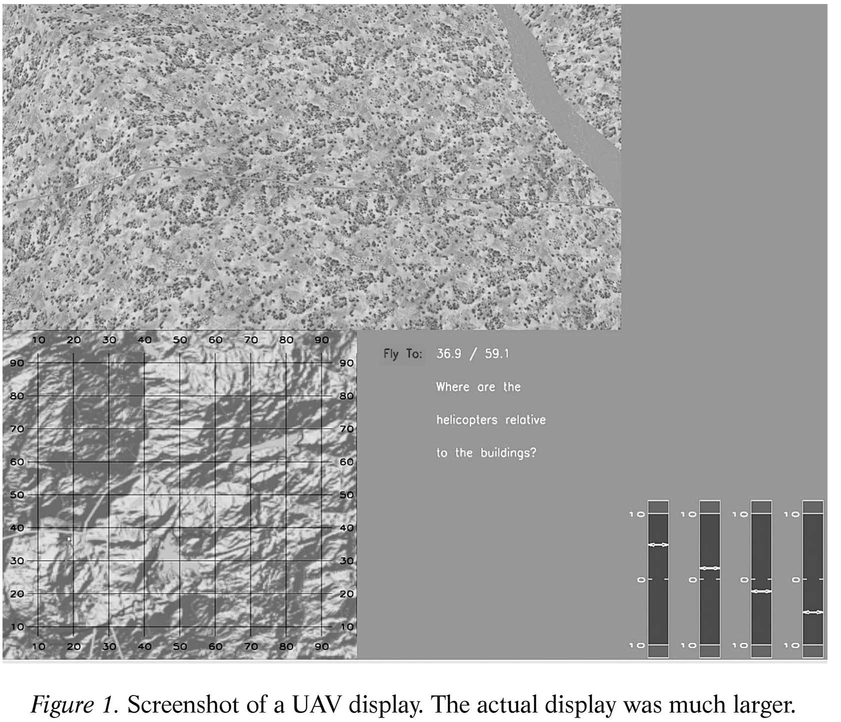

Figure 1. Screenshot of a UAV display. The actual display was much larger.

autoalert conditions, pilots were required to continuously navigate the UAV by twisting the joystick around a longitudinal axis running down the handle, allowing them to aim the UAV in the desired direction through first-order control of heading, perturbed occasionally by crosswinds. All other aspects of flight control (pitch, bank, etc.) were automated, with airspeed and altitude fixed at 70 knots and 6000 feet, respectively. The autoalert condition augmented the baseline condition by providing auditory alerts when system failures occurred as well as auditory presentation of command target location and report instructions. The autopilot condition augmented the baseline condition by allowing pilots to simply enter fly-to coordinates on a keypad, which enabled the computer to guide the UAV in a straight-line path to the next command target (CT).

Target Search and Report Tasks

Pilots flew 10 straight flight legs. At the end of each leg, pilots inspected a CT and responded verbally to specific report questions regarding the placement of military vehicles around the buildings (e.g., "What weapons are located on the south side of the building?"). These targets consisted of a building (factory, hangar, etc.) with one to three tanks and/or helicopters located randomly around the building. Upon reaching each CT, pilots entered the high-workload image inspection phase, in which they were required to loiter while zooming and panning the image camera in order to report the locations of these weapons systems, specified in cardinal directions. This forced a relatively high level of spatial-cognitive activity (e.g., Gugerty & Brooks, 2001). Along each leg, pilots were also instructed to search for well-camouflaged TOOs. Each TOO was of approximately 1° to 2° visual angle and was always located between 20% and 80% of the distance traveled between CTs. Around each TOO were one to three tanks and/or helicopters, and pilots were required to report what they saw.

System Monitoring Task

During each mission, pilots were required to monitor the system gauges and detect SFs when they occurred. Each SF lasted 30 s, after which it would return to normal. Upon detection of an SF, pilots indicated which SF gauge had failed (i.e., 1–4) by pressing the corresponding button on the keypad and then typed in current ownship coordinates of the UAV, again using the keypad numbers and "enter" key. SFs were positioned so that they occurred under two different levels of concurrent demand within a UAV workstation: during simple tracking (low workload) and during CT or TOO image inspection (high workload). Every leg contained at least one SF but not more than three.

Procedure

Participants spent 10 to 15 min becoming familiar with the controls and viewing sample targets and SFs before beginning the approximately 1-hr experimental session. Although they were instructed that performance bonuses were rewarded based on a combination of performance in all tasks equally, pilots were free to choose their own strategies for target search and system monitoring.

Design

A counterbalanced 3 (between-subjects) × 2 (within-subjects) mixed model design was employed in which each of the 36 pilots was randomly assigned to a given condition (baseline, autoalert, or autopilot), with the constraint that there were to be 12 pilots in each condition. Each pilot encountered both a single- and a dual-UAV flight control. The order of single- and dual-UAV trials was counterbalanced, with half the pilots flying a single-UAV mission followed by a dual-UAV mission, and vice versa.

RESULTS

Mixed-design statistics were employed to analyze the data (between conditions and within number of UAVs); because of missing data points, there are sometimes different degrees of freedom in the analyses of variance (ANOVAs). Table 1 presents an overview of the data across both single- and dual-UAV flight controls.

Mission Completion

Navigation task. Tracking error obviously benefited from the autopilot (error was zero) but not from the autoalert offload, $F(1, 20) < 1.0$, and was not affected by the number of UAVs, $F(1, 20) < 1.0$. CT response times and report

TABLE 1: Mean Performance for All Major Tasks

	Single			Dual		
	Baseline	Autoalert	Autopilot	Baseline	Autoalert	Autopilot
Tracking error (RMS; meters)	2785	2775	0.00***	2796	2766	0.00***
CT report time (s)	28.77	21.85	21.23	29.06	26.91	25.58
CT report accuracy (%)	86	86	89	92	78	88
No. of repeats (per leg)	2.90	1.78**	1.50***	4.16	3.13**	1.88***
TOO detection rate (%)	57	45	92***	40	28	79***
TOO report time (s)	18.84	19.87	18.85	22.32	20.97	17.42
TOO report accuracy (%)	79	75	89	77	71	90
SF detection rate (%)	85	92	93	73	98*	83
SF detection time (s)	7.16	3.58***	8.31	10.91	3.91***	11.19
SF report accuracy (%)	90	93	93	90	97	88

Note. RMS = root mean square, CT = command target, TOO = target of opportunity, SF = system failure.
*$p < .05$, **$p < .01$, ***$p < .001$ (contrasts with baseline performance).

accuracy did not differ significantly across any of the conditions or flight controls (all $ps > .10$; note that in Table 1, there does appear to be a somewhat negative effect when going from single-UAV to dual-UAV performance, especially in the autoalert condition).

Repeats. As mentioned previously, pilots were allowed to refresh their memory for the flight and CT instructions by pressing a repeat key. Repeats were used as an implicit measure of flight instruction memory failures. An ANOVA revealed a main effect of condition, $F(2, 33) = 16.31$, $p < .001$, and number of UAVs, $F(1, 33) = 43.18$, $p < .001$; however, a significant interaction between condition and number of UAVs, $F(2, 33) = 4.08$, $p < .05$, suggests that the autopilot condition did not suffer as much (require more repeats) in the dual-UAV trials as did the baseline and autoalert conditions. The advantage of the autopilot condition over the baseline condition, $F(1, 22) = 27.28$, $p < .001$, probably indicates an indirect result of the reliable autopilot feature; that is, pilots did not need to refresh their memory for the fly-to coordinates, given that these were programmed into the autopilot at the outset of each leg. The auditory autoalert condition showed fewer repeats as compared with the baseline condition, $F(1, 22) = 7.78$, $p = .01$, suggesting more efficient parallel processing, which is perhaps attributable to the use of separate modalities (Wickens, 2002).

Target of opportunity (TOO) monitoring. The autopilot condition facilitated higher TOO detection rates as compared with the baseline condition, $F(1, 22) = 25.0$, $p < .001$, whereas no improvement was seen for the autoalert condition relative to baseline, $F(1, 22) = 1.47$, $p = .24$. This autopilot benefit for TOO detection can be explained by a reduction in tracking workload, which allowed pilots to reallocate perceptual resources to the TOO monitoring task. TOO detection rates dropped by 20% to 30% in the dual-UAV condition, as compared with the single-UAV condition, $F(1, 33) = 20.01$, $p < .001$, and did so to an approximately equivalent extent for all three conditions, $F(2, 33) < 1.0$, $p > .10$. Neither TOO report times nor TOO report accuracy appeared to benefit from either the autoalert or autopilot offloads (all $ps > .10$).

System failure (SF) monitoring. With regard to SF detection rates, the autoalert condition revealed benefits over the baseline condition, $F(1, 22) = 5.29$, $p = .03$, whereas the autopilot condition provided no significant benefits relative to baseline, $F(1, 22) = 1.38$, $p = .26$. With regard to SF detection times, the autoalert condition was faster than baseline, $F(1, 17) = 25.88$, $p < .001$, whereas no improvement was seen for the autopilot condition over baseline, $F(1, 18) < 1.0$. Because of the absence of autopilot benefits, further analyses were done only on differences between the baseline and autoalert conditions.

Figure 2 presents detection times broken down according to the workload of the concurrent flight control task for the baseline and auditory autoalert conditions; the left side represents SFs detected during simple tracking

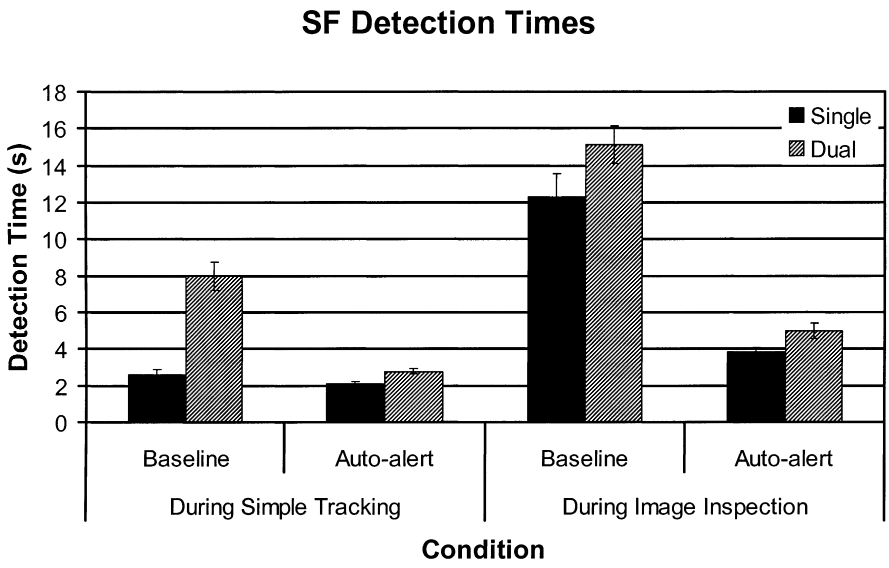

Figure 2. SF (system failure) detection times across condition and workload of side task. The left side represents the difference between conditions during low-workload simple tracking, while the right side reflects the difference between the same conditions during high-workload image inspection. Standard error bars are included.

(low workload), and the right side presents SFs detected during target image inspection (high workload).

A main effect of load, $F(1, 17) = 37.0$, $p < .001$, indicates that the high-workload condition suffered relative to the low-workload condition; however, an interaction between load and condition, $F(1, 17) = 13.28$, $p < .01$, reveals a much larger penalty for the baseline condition during high-workload situations. A main effect of number of UAVs, $F(1, 17) = 7.91$, $p = .01$, indicates that the dual-UAV situations suffered relative to the single-UAV situations; however, a marginally significant interaction between condition and number of UAVs, $F(1, 17) = 3.42$, $p = .08$, suggests that the autoalert condition did not suffer as much in dual-UAV flight control as the baseline condition did and, indeed, did not appear to suffer at all in dual-UAV relative to single-UAV conditions. In other words, with the aid of the autoalert system, pilots were able to detect system failures almost as quickly during dual-UAV control as during single-UAV control, with very little performance drop even during the most difficult concurrent task (i.e., target inspection). There was no significant interaction between load and number of UAVs, $F(1, 17) < 1.0$. SF report accuracy did not benefit from either form of offload, $F(2, 32) < 1.0$.

DISCUSSION

In the following, we review how the requirements of piloting both single and dual UAVs, as mitigated by automation assistance, affected the workload imposed on pilots. Although we recognize that "workload" is a multifaceted construct, we focus here only on the most critical performance-based index of dual-task workload – that is, the loss of performance from its perfect or single-task level, imposed by the diversion of resources to concurrent tasks. For any given task in our simulation, this diversion could be imposed by up to five concurrent tasks, depending on whether or not tracking was automated and whether one or two UAVs were flown (the maximum of five tasks, concurrent with the measured task, occurs in the dual-task baseline condition). We address the workload issue in the following sections, in the order of the criticality of the three major tasks to mission success.

Mission Success: Navigation and Command Target Report

The first issue examined was the extent to which the primary tasks involved with mission success were protected from the effects of concurrent task load. Although tracking (navigational) task performance was not as proficient manually as with the perfect autopilot, it is nevertheless clear that pilots protected this task from interference with all others, regardless of whether or not the autoalert system was present and whether one or two UAVs were controlled. Therefore, even during dual-UAV flight control, tracking did not suffer a workload-imposed decrement. Furthermore, the other important index of mission success, the reporting of command targets, although not perfect (given the high cognitive demands of mental rotation and close image inspection; Gugerty & Brooks, 2001), was nevertheless not significantly affected by the requirements of concurrent task load. Thus pilots were somewhat effective in protecting this most important aspect of their mission from resource competition, even when controlling two UAVs, just as manned aircraft pilots tend to be optimal in protecting the primary tasks of aviating from competing demands of lower priority tasks (Damos, 1997; Raby & Wickens, 1994; Wickens, Goh, Helleberg, Horrey, & Talleur, 2003). It is important to note that pilots sometimes achieved this primary task performance protection by increasing the number of times they refreshed their memory for the flight instructions as the workload demands increased, both in the baseline condition and in the autoalert condition.

Mission Support: The System Monitoring Task

In real UAV flight, a pilot's failure to quickly detect system failures could compromise mission completion in a timely fashion or, perhaps, jeopardize the mission entirely. Here performance was vulnerable even with single-UAV requirements and even with the aid of automation; that is, perfectly reliable automation did not prevent performance decrements in the system monitoring task, although the auditory alerting aid enabled pilots to perform better than baseline (i.e., no automation aid). The task of simply monitoring for variables to cross the system threshold "failure" line (bottom right panel of Figure 1) is easy enough that it could be carried out at 100% accuracy and minimal (<1 s) latency if there were no other visual requirements. However, the single-UAV data (Table 1) show a 7% accuracy loss (from 100%) in the autopilot condition when pilots were required to monitor only the 3-D image window and a 15% loss when this requirement was coupled with the need to monitor the tracking display in the single-UAV baseline condition. Both of these decrements were essentially doubled in dual-UAV conditions. Furthermore, the latency of detecting those failures that were noticed increased in a corresponding fashion, particularly when pilots were engaged in the heavy demands imposed by image inspection (Figure 2).

Notably, the presence of the auditory tone to alert pilots of the failures greatly reduced these decrements and indeed, in the dual-UAV condition, rendered them at a level at which one might classify them as being unaffected by task loading. Therefore, we conclude that the demands of monitoring multiple displays, particularly when navigating two UAVs, are so great that performance decrements are almost unavoidable in the system monitoring task; however, perfectly reliable auditory alerts can help to alleviate some of these decrements, compared with baseline, and allow operators to better control and supervise both the primary mission and mission support tasks of one and even two UAVs.

Surveillance and TOO Detection

The relatively optimistic picture painted in the preceding sections, regarding primary mission success supported by automation, is greatly tempered when performance of the third task, monitoring for TOOs, is considered. In its single-task rendering this is a high-workload task, subjectively rated at over twice the workload as monitoring the tracking or visual system displays (Dixon & Wickens, 2004). Even though TOO detection can be performed rapidly and with perfect accuracy when no other task is present (Dixon & Wickens, 2003), in the current study that performance was devastated by the addition of any other tasks. Even in the best-case condition of single-UAV autopilot tracking (when the navigation task did not need to be monitored), the visual demands imposed by system failure monitoring dropped the detection rate of TOOs in the 3-D image window to 92%. As indicated in Table 1, the additional imposition of navigation monitoring demands (baseline) and/or dual-UAV control (in all three interface conditions) severely compromised pilots' ability to engage in surveillance, sometimes dropping detection rates below 50%. It is interesting to note that although single versus dual operator effects were not evaluated in the current study, some of these decrements may be attributable to such effects. As mentioned in the Introduction, in current U.S. Army operations each UAV team consists of two operators, one responsible for navigating the UAV and the other for handling the target search and image inspection tasks. We found that a single pilot, who was responsible for the duties of both operators, had significant performance decrements in the target search task, even when handling only one UAV.

Modeling Efforts for Practical Design

The current results have implications for developing computational models of multitask interference (Liao & Moray, 1993; Sarno & Wickens, 1995; Wickens, 2002), which are described in detail in Dixon et al. (2003). Briefly, these data suggest that single-channel assumptions regarding workload predictions (Liao & Moray, 1993) are adequate only when a fully visual interface is employed, and such models do not account for data that describe the performance gains associated with auditory alerts and command target information. Such benefits appear to be better accounted for by multiple-resource models (Meyer & Kieras, 1997; Sarno & Wickens, 1995; Wickens, 2002).

Conclusion and Further Research

On the one hand, we argue that the automation aids used in the current study can have positive effects on performance, even during multiple-UAV flight control. The auditory alert system benefited performance above baseline in the system monitoring task for both the single-UAV and dual-UAV conditions. An added bonus was a reduction in the number of times pilots had to refresh their memory for the flight instructions, relative to baseline, indicating that the pilots were able to use auditory resources to better understand the command target instructions in this otherwise highly demanding visual environment. The autopilot system, as expected, benefited performance in the primary navigation task and, furthermore, enabled pilots to detect more targets of opportunity by reducing overall workload levels and allowing pilots to reallocate resources to the image display window. On the other hand, the automation aids presented here may not be the panacea that designers often hope for, particularly during multiple-UAV flight control. Although the handling of multiple displays in a single UAV did not appear to seriously damage performance relative to single-display conditions, pilots suffered more decrements during dual-UAV flight control, even when they were supported by the automation aids. Apparently, the workload imposed by having to monitor up to eight displays simultaneously was too great to overcome with only two automation aids.

One criticism of the study is that it may not have incorporated all the tasks required of UAV pilots in the real world. For example, constant communication between pilots and other personnel (intelligence, ground station, other vehicles, etc.) often requires pilots to respond and/or replan and retarget, adding additional workload issues not discussed here. These additional dynamic issues may intensify the demands made on pilots, causing further performance decrements, which could be exacerbated under multiple-UAV conditions.

A second criticism of the study is that flight students with little specific UAV training were employed as participants and that this sampling may underestimate the multitasking capabilities of the U.S. Army specialists to whom this research is intended to generalize. This potential effect may have been offset by the fact that both forms of automation were imposed under best-case scenarios, when automation was perfectly reliable, and therefore did not need to be monitored for possible failures. However, just as UAVs themselves are vulnerable to system failures, the automation that is imposed to assist human performance may also be imperfect. Detection systems such as the autoalerts used here are prone to both misses and false alerts (Dixon & Wickens, 2004; Maltz & Shinar, 2003, Meyer, 2004), and even autopilots may sometimes be perturbed (Ephrath & Curry, 1977). Hence, we must temper the conclusions that automation of even a single UAV will adequately support the primary mission and mission support tasks if that automation is imperfect. Indeed, current data suggest that it may not (Dixon & Wickens, 2004).

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