THE EFFECTS OF VIDEO FRAME DELAY AND SPATIAL ABILITY ON THE OPERATION OF MULTIPLE SEMIAUTONOMOUS AND TELE-OPERATED ROBOTS

by

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ABSTRACT

The United States Army has moved into the 21st century with the intent of redesigning not only the force structure but also the methods by which we will fight and win our nation's wars. Fundamental in this restructuring is the development of the Future Combat Systems (FCS). In an effort to minimize exposure of front line soldiers the future Army will utilize unmanned assets for both information gathering and when necessary engagements. Yet this must be done judiciously, as the bandwidth for net-centric warfare is limited. The implication is that the FCS must be designed to leverage bandwidth in a manner that does not overtax computational resources. In this study alternatives for improving human performance during operation of teleoperated and semi-autonomous robots were examined. It was predicted that when operating both types of robots, frame delay of the semi-autonomous robot would improve performance because it would allow operators to concentrate on the constant workload imposed by the teleoperated while only allocating resources to the semi-autonomous during critical tasks. An additional prediction was that operators with high spatial ability would perform better than those with low spatial ability, especially when operating an aerial vehicle. The results can not confirm that frame delay has a positive effect on operator performance, though power may have been an issue, but clearly show that spatial ability is a strong predictor of performance on robotic asset control, particularly with aerial vehicles. In operating the UAV, the high spatial group was, on average, 30% faster, lazed 12% more targets, and made 43% more location reports than the low spatial group. The implications of this study indicate that system design should judiciously manage workload and capitalize on individual ability to improve performance and are relevant to system designers, especially in the military community.

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER ONE
INTRODUCTION

The rapid growth in computing and robotic abilities has lead to a proliferation of autonomous or semi-autonomous vehicles, yet the concept of human-robot interaction (HRI) is relatively young (Scholtz, 2003). In general terms, engineers and designers have moved forward very rapidly in the development of sophisticated and complex systems while underestimating the need for research concerning the human-machine interface (Woods, Tittle, Feil & Roesler, 2004). As machines become more complex there is an increased need for a thorough understanding of the limits of the man-machine team. With the demise of the Soviet Union and the end of the cold war the United States remains the world's only superpower. With this hegemony comes responsibility. The United States Army has moved into the 21st century with the intent of completely redesigning not only the force structure but also the basic methods by which we will fight and win our nation's wars (Shinseki, 1999). Fundamental in this restructuring is the development of the Future Combat Systems (FCS). The FCS is an integral part of the net-centric, asymmetric battlefield of tomorrow and within the FCS the efficient and effective deployment of autonomous and semi-autonomous platforms is prolific. In an effort to minimize the exposure of front line soldiers while simultaneously fighting an enemy that is often embedded within an indigenous population the future Army will utilize unmanned assets for both passive and active information gathering and when necessary direct or indirect engagement. Yet this must be done judiciously, as the computational bandwidth for net-centric warfare is limited. The implication is that the FCS must be designed to leverage bandwidth in a strategic manner, one that does not overtax computational resources.

Additionally the Army is interested in reducing the total number of soldiers on the battlefield. To this end it is likely that military robotic operators will be required to operate more than one asset at a time. The control of multiple assets is rarely studied and in need of detailed attention. The ability of a single operator to control multiple differing assets will depend upon the careful integration of the assets and thorough examination of workload implications. This study will review different types of robots (teleoperated vs. semi-autonomous), discuss the human performance implications of operating multiples, and offer alternatives for improving operator performance.

CHAPTER TWO
LITERATURE REVIEW

Robot Type

In the discussion of HRI it is important to first differentiate between different types of robots and different modes of operation. Recognizing these differences is key to understanding the complexity of multi-robot control. The first distinction is between autonomous and teleoperated vehicles. Autonomous vehicles are given a set of orders or commands then can be left alone to operate those commands. The systems used to operate these machines are analogous to the auto-pilot controls on modern airplanes. Baring serious changes in mission parameters or malfunctions, such vehicles are expected to proceed without much human intervention. Teleoperation requires direct operation at a distance with the operator responsible for all cognitive processes (Malcom & Lim, 2003). This mode is exemplified by underwater robots used for deep water research. Teleoperation augments a human operator's strength and range, while simultaneously insulating him from immediate harm (Lapointe, Robert & Boulanger, 2001); while autonomous vehicles attempt to augment human cognition and aid decision making. The Army's intent is to couple both types of robots under one operator.

Teleoperation

A teleoperated vehicle uses onboard sensors and communication links to allow a human operator to control the vehicle from a distance. Teleoperated vehicles range from common four degree of freedom (DOF) manipulated construction vehicles (backhoe, excavator, forestry harvester, and mining drillers) to complex systems that operate at great distances from the operator (deep sea remote vehicles, mars rover). Remote perception and remote manipulation are the two primary human performance issues relating to teleoperated vehicles.

Remote perception

"Perception is the process of making inferences about distal stimuli (objects in the environment) based on proximal stimuli (energy detected by sensors)" (Fong et al., 2004, p3). Remote perception involves making such inferences when the stimuli are out of range of the human senses. Remote perception requires that a human leverage electronic sensor data to interpret and make sense of perceived stimuli. It can be subdivided into two areas, passive and active perception.

Passive Perception is the interpretation of sensor data and involves *identification* (the detection and recognition of mission related objects), *judgment of extent* (absolute and relative judgments of distance, size, or length), and *judgment of motion* (estimates of the velocity of egomotion or movement of other objects).

Active Perception, on the other hand, is the deliberate action involving sensor manipulation to gain information about the environment and involves *active identification* (recognition tasks that involve mobility and/or manipulation of the camera), *stationary search* (search tasks that do not involve mobility but usually involve camera control or data fusion from sensors), and *active search* (search tasks that involve mobility and usually involve camera control or data fusion from sensors). Operators of teleoperated vehicles must be capable of both passive and active perception, however, these perceptual activities can be challenging. For example: because a robot separates the operator from the environment, there is often a disconnect between an operator's remote perception of the environment and reality (Wood et al., 2004). This separation leads to among other things, problems with scale ambiguity, rate of motion, and tunnel vision. These generally occur because the operator is removed from the dynamic environment and thus fails to grasp the natural relationships afforded by true immersion in an environment. Specifically, robotic cameras offer a limited visual field and completely remove an operator from the physical cues (i.e. proprioceptive and vestibular cues) normally afforded by an environment. These issues often result in inaccurate mental models of the environment, missed events and poor spatial awareness (Darken & Peterson, 2002). Additionally degradation in depth perception caused by the monocular cues associated with robotic cameras affect an operator's ability for accurate distance estimation and depth perception. Employing multiple camera angles can offer both ego- and exocentric views but the additional cognitive recourses needed to interpret such differing views can often confound their benefits (Olsen & Goodrich, 2003). Additionally, it is suggested that switching between different camera viewpoints may induce motion sickness (Van Erp & Padmos, 2003). Further, the time and effort needed to switch between views; coupled with the need to remember the environment associated with each view can be a drain on human performance (Casper & Murphy, 2003). Taken together, these studies suggest that remote perception via teleoperated robots is a challenge with current technology (see Table 1).

Table 1
Issues with Robots by Type

Robot Types	Issues
Teleoperated	Continuous workload Scale ambiguity Rate of motion Tunnel vision Loss of physical cues Issues with distance estimation and depth perception Limited field of view Frame rate Operator platform movement
Semiautonomous	Intermittent workload Situational awareness Complacency Skill degradation

<u>Remote Manipulation</u>

Remote manipulation involves: navigation (i.e. manipulating an asset along a specified route) and manipulation tasks (i.e. maneuvering a remote arm or sensor for detailed, discrete actions) (Fong et al. 2004). These activities also impose human performance issues during teleoperation. Specifically, a limited field of view can compromise driving performance as demonstrated by studies that examine peripheral vision and lane deviations (Van Erp & Padmos, 2003). Frame rate can also be an issue. The degradation of a video image below 8 frames per second (2 or 4 fps) has been shown to increase navigation times, but not navigation errors, target identification or situational awareness (French, Ghirardelli, & Swoboda, 2003). However, it has been demonstrated that frame rates above 8 fps do little to enhance driving performance (McGovern, 1991 as cited in Van Erp & Padmos, 2003). Motion of an operator's platform while manipulating a remote asset has been shown to make tasks harder and some tasks, specifically target acquisition, nearly impossible (Kamsickas, 2003). These issues of manipulation add to the complexity of teleoperated assets (see Table 1).

Semi-autonomous

Semi-autonomous robots execute simple commands from an operator without constant interaction. Generally these commands are navigational in nature (i.e. fly from point A to point B). The primary human performance issues with automation in general, and semi-autonomous vehicles in particular, are mental workload, situational awareness, complacency, and skill degradation (Parasuraman, Sheridan & Wickens, 2000).

Mental Workload

Well designed automation can reduce an operator's workload. Examples of this are often found in the aviation community. Air traffic controllers now receive graphical information about pertinent airplanes vs. textual data that requires more mental processing (Vicente & Rasmussen, 1992). However, automation that does not properly match an operator's mental model or is difficult to initiate or engage can increase cognitive workload. In particular, semi-autonomous vehicle control is likely to cause intermittent periods of higher workload (Kirlik, 1993). The intermittent higher workload is associated with target identification and location reporting tasks, which involve moments of acute focus. These tasks are the primary responsibilities of robot assets. During target acquisition the semiautonomous robot highlights possible targets but it takes active steps by the operator to identify and take appropriate action (destroy or bypass). To maintain positive control over battlespace current locations of all friendly assets is essential. The semiautonomous robot can maneuver to a designated position but the operator must confirm and then report those locations. Outside of these activities, however, there is little demand on the operator. In terms of semi-autonomous robot control the implications is that if an intermittent workload placed on operator is judiciously managed the workload is acceptable, however is the coordination of this workload conflicts with other requirements the operator may be overwhelmed.

Situational Awareness

As automation increases it can have negative effects on an operator's situational awareness. "Humans tend to be less aware of changes in environmental or system changes when those changes are under the control of another agent" (Parasuraman et al. 2000, p.291). Endsley (1995) found that when an operator is a passive observer, as is the case with semi-autonomous vehicle control, it becomes challenging to understand, learn, and remember consequences of different actions; thus this can hinder the development of an accurate mental model. The implications of this are that in a tactical environment where situational awareness is paramount, the introduction of automated decision making, may do more to hinder the overall mission success by removing an operator from the decision making loop. If the automated asset executes actions without human input the human may not realize that actions were taken or develop an understanding of the consequences of those actions.

Complacency

If a system is reliable but not perfect errors can occur from an operator's over trust (Parasuraman, Molloy & Singh, 1993). Due to such complacency, automation can cause vigilance decrements (i.e., decreasing ability to maintain attention during monitoring). Specifically, if automation is generally reliable and predictable, then operators tend to monitor the automation with less vigilance (Dzindolet, Pierce, Beck, & Dawe, 1999), which can lead to error. These complacency errors can result in missed information i.e. the system fails to alert on a possible target, or incorrect information i.e. the system alerts on an object that is not a target. In either case if an operator has become accustomed to the system doing the job and does not verify the presented information, errors may occur.

Skill Degradation

There is extensive research documenting that without maintenance skills degrade (Rose, 1989; Parasurman et al., 2000). This is applicable to semi-autonomous robots because as robots assume a greater portion of mission tasks, as needed to allow an operator to simultaneously control multiple assets, that operator's skills on individual tasks may decrease. The implications being if an operator is required to perform a task that has been handled by automation errors may occur.

Human Performance Implications of Operating Multiple Robot Assets

The issues associated with teleoperated vs. semi-autonomous robots appear very different (see Table 1). Specifically, teleoperated robots require constant control for sensor manipulation and navigation. This yields a consistent workload demand with issues of rate of motion, scale ambiguity and field of view. On the other hand, the nature of operating a semi-autonomous robot is intermittent workload with issues in situational awareness, complacency, and skill degradation. The only apparent common concern is workload and even here, it appears that the continuous workload of the teleoperated robot might plausibly be coupled with the intermittent workload associated with semi-autonomous vehicles. However, to gain a more complete understanding of the implications on operator performance, these issues must be analyzed from a human performance perspective.

An examination of the human performance issues associated with controlling multiple robotic assets can be conducted under the framework of Human Information Processing (HIP) (Wickens & Hollands, 2000). This model has two primary properties, first is that processing occurs in stages and second, that constant feedback suggests that the there is no clear starting point in the HIP loop. This model aids in understanding the psychological processes involved during interaction with a system. Miller (1956) demonstrated that short term memory was limited in both size and duration; Baddeley (1986) modified the concept of short term memory into the now common two component model of working memory (i.e., verbal [phonological loop] and spatial [visual-spatial sketchpad]) and discussed how each modality-specific subsystem can act as an HIP bottleneck due to its limited capacity.

Knowing that working memory can limit an operator's performance during complex tasks, robotic systems should be designed with an understanding of these limitations. The above discussion of issues relating to robotic control (see Table 1) would suggest that an operator can manipulate different types of assets (teleoperated and semiautonomous) without a conflict as long as workload is judiciously allocated. The issue becomes how to manage this workload.

The first step in managing workload is to understand the kind of load being imposed via the control of each robot asset. The mode for presenting information during control of either type of robot is primarily restricted to the visual-spatial channel. Specifically, the primary source of information used in control of both types of robots is that obtained via video screens. A teleoperated robot uses screens to display information about a vehicle's current status along with screens to display the robot's environment. Likewise, semi-autonomous robots utilize video screens to display both status and environment. Much of the information flow is thus visual-spatial in nature, which can pose a daunting load on spatial working memory. To manage the workload associated with multiple robot asset control, means of reducing this visual-spatial load through systematic system design are needed. However, one must also consider the abilities of the operator in order to achieve an optimal coupling of human and system.

One individual factor that is particularly relevant to human performance with multiple robotic assets is spatial ability. Spatial ability is the ability to navigate or manipulate objects in a three-dimensional (3-D) space (Eliot, 1984). Existing research generally divide spatial ability into two categories, visualization and orientation (Salzman, Dede & Loftin, 1999; Lathan & Tracey, 2002 and Hegarty & Waller, 2004). Although spatial ability is often divided the two categories are highly correlated (Hegarty &Waller, 2004). There is, however, a division of visualization that may be particularly relevant to robotic control, that of egocentric vs. exocentric visualization (Salzman et al. 1999). Egocentric is a self-centered view and most individuals, whether with high or low spatial abilities, are comfortable viewing the world from this familiar position. However, an exocentric or outside view is generally easier for high spatial to acquire than low spatial individuals (Salzman et al. 1999). These differing views, and the ability to interpret data from them, have specific implications for operating robotic assets.

The differences here have less to do with the robots operating mode (teleoperated or semi-autonomous) but more to do with the perspective (ground or aerial). An aerial vehicle will provide an exocentric view in 3-D space and the ground based operator must translate this view into an egocentric view in order to direct its operation. This ability to visualize a ground battle environment from an aerial perspective will likely be more difficult for low spatial ability individuals. However, spatial ability may also affect ground-based vehicles, but likely to a lesser extend as such vehicles only have to be manipulated in two-dimensions. For example, Lathan (2002) demonstrated that individuals with high spatial abilities performed better in control of teleoperated ground-based robots.

<u>Alternatives for Improving Human Performance</u>

The current problem associated with multiple robotic asset control is suggested to be an overload on visual-spatial processing. Both types of assets (teleoperated and semi-autonomous) are primarily controlled through video screens. Two approaches to reducing this current bottleneck are proposed: multiple channels and synchronizing the load.

Multiple Resource Theory (MRT) (Wickens, 1991) offers options for enhancing human performance during multitasking activities, such as the simultaneous operation of multiple robotic assets. According to MRT, by presenting information in different modes (i.e. spatial vs. verbal) an operator can draw from separate HIP resource pools, thereby providing a greater overall capacity to process and respond.

Knowing that human performance is likely to be degraded when operating multiple robots because of a strain on visual-spatial resources; the opportunity exists to offload some of the encoding and processing through the use of multiple channels. Specifically, MRT suggests a potential method for improving performance by utilizing additional modalities (Wickens, 1991). It may be possible to move some information presentation from the visual-spatial video screens to audio-verbal or even haptic channels. The result may be improved human performance because of a distribution of workload across multiple working memory subsystems. However, this alternative may be too costly in terms of bandwidth in an already crowded net-centric battlefield. Attempts to augment data transmission through alternative modality-based channels may result in delays in the network or possibly dropped data. Current data transmission technology may not allow for this alternative. Thus, in the bandwidth restricted, net-centric battlefield, increasing the channels of information that can be conveyed to an operator may not be feasible. Therefore other alternatives should first be explored.

By capitalizing on the inherent nature of the two different types of robotic assets, it may be possible to improve performance by synchronizing the workload imposed by each while minimizing bandwidth demands on the net-centric battlefield. As previously discussed, teleoperated vehicles pose a constant workload, while semi-autonomous vehicles pose an intermittent workload. It may be possible to leverage this difference by degrading the visual-spatial information flow associated with the semi-autonomous vehicle, thereby reducing visual-spatial workload, and only draw attention to that asset at critical times (target identification and location reporting). Attention could be drawn by adding an auditory alert (based on MRT) and then enhancing the visuals for the semi-autonomous vehicle during these critical tasks. There is no need to focus attention on the semi-autonomous vehicle accept during critical task periods. The degraded visuals should draw attention away from the screens associated with the semi-autonomous vehicle, thus facilitating multitasking with the teleoperated vehicle. Although the auditory alert would be an ideal cue, for this study the semiautonomous robot will use a highlighted graphic cue to draw attention when needed. This is similar to graphical level-of-detail manipulations, which provide greater graphical detail only when needed (Park & Kenyon, 1999). The objective is to reduce visual-spatial workload during multitasking of teleoperated and semi-autonomous vehicles by degrading visuals for a semi-autonomous vehicle (an existing side effect of limited bandwidth) during non-critical operating periods and drawing attention to the semi-autonomous vehicle via a visual alert only during critical task periods.

Hypothesis

First

Multitasking of teleoperated and semi-autonomous vehicles will be enhanced by degrading visuals for a semi-autonomous vehicle during non-critical operating periods and drawing attention to the semi-autonomous vehicle via a visual alert only during critical task periods.

Second

Operators with high spatial ability will perform better at robotic tasks; especially in the UAV scenario because of the 3-D exocentric nature of the asset.

CHAPTER THREE
METHODOLOGY

Participants

Thirty participants (11 females, mean age 21, standard deviation 4.07, range 15 [18-33]; 19 males, mean age19, standard deviation 1.9, range 6 [18-24]) were recruited from the University of Central Florida. 25 of the 30 participants self reported being at least good with computers, 4 reported as excellent and 1 expert. 27 of 30 reported playing at least some video games. 27 participants are undergraduate students; the remaining 3 are graduate students. Participants received either class credit or $50 for participating in the experiment.

Apparatus

All training and testing was conducted on the Embedded Combined Arms Team Training and Mission Rehearsal Simulator at the Simulation and Training Technology Center, Orlando. This test bed simulator is a one person crew station from which a human operator can simulate the control of one teleoperated vehicle and several semi-autonomous vehicles. The teleoperated vehicle is similar to a small tank that is remotely operated through a yoke control and two pedals. Information is relayed about this vehicle through the use of three touch sensitive screens. The semi-autonomous vehicles are either ground or air and are given executable commands through a touch sensitive screen. The Operator Control Unit (OCU) consists of six, touch sensitive display screens (see figure 1), a control yoke, foot pedals, and trackball. It was developed and built under a joint program between the Institution for Simulation and Training (IST) at the University of Central Florida, and the Army Research Lab (ARL).

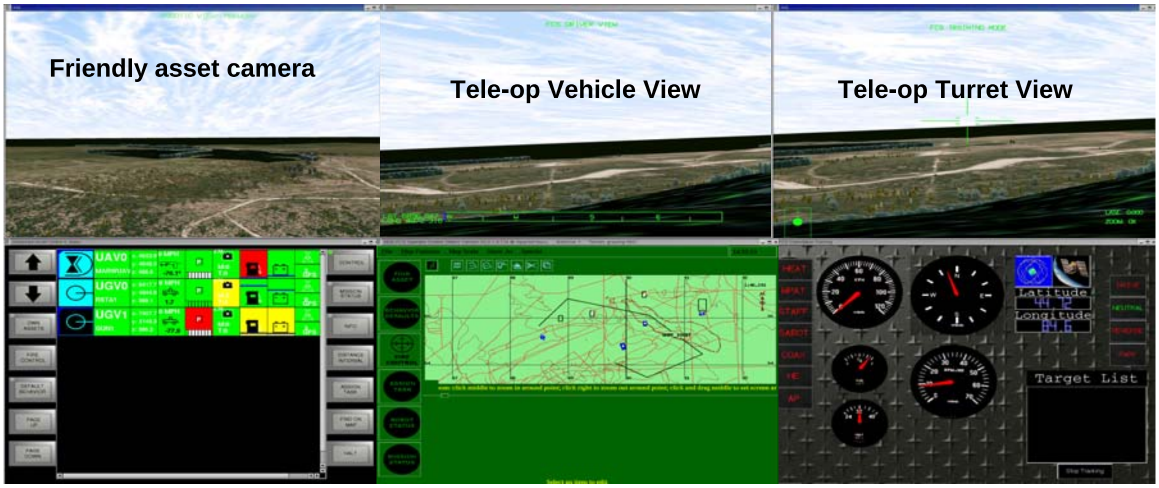

Figure 1: User interface of ECATT-MR C2V testbed

Questionnaires

The Cube comparison test (Educational Testing Service, 1976; Ekstrom, French, & Harman, 1976) was administered to participants prior to executing the scenarios. This test assesses an individual's spatial ability by requiring them to compare 21 pairs of six-sided cubes and determine if the rotated cubes are the same or different. Participants are given three minutes to perform this task. Scores are derived by subtracting the number wrong from the number correct. Blank questions are ignored. The results are used to designate a participant as having either good or poor spatial ability.

A test for perceived workload (NASA TLX) was administered at the end of each scenario (four times) throughout the experiment. This questionnaire is a self-reported questionnaire of perceived demands in ten areas: mental, physical, temporal, effort (mental & physical), frustration, performance, visual, cognitive, and psychomotor. Each demand component is scaled from 1-10.

A simulator sickness questionnaire (SSQ) was administered at the end of each scenario (four times) throughout the experiment. This test is used to assess the participants overall discomfort level and is comprised of a checklist of 26 symptoms. Each symptom is related in terms of degrees of severity (none, slight, moderate, severe). The SSQ provides a Total Severity score obtained by a weighted scoring procedure (Lane & Kennedy, 1988).

Tasks

Participants were required to conduct a route reconnaissance on four separate routes with differing robotic assets. Prior to the experiment each participant received three hours of training one week before and a one hour refresher immediately before the experiment. All participants were tested on their level of ability as part of a separate learning experiment prior to the start this experiment. Each mission lasted no more than 30 minutes. The primary tasks were maneuvering the robot(s) from an Assembly Area (AA), along a designated route, to a Release Point (RP); finding, lazing, and reporting any enemy forces encountered along the route; and providing location reports upon arriving and departing each checkpoint. The first three missions were conducted with a single differing robotic asset and the fourth mission combined the use of all three types of robots (teleoperated, semi-autonomous ground, and semiautonomous air). Each of the four routes (i.e., scenarios) were designed the same, accounting for length, terrain, number of enemy, and number of checkpoints.

Asset Conditions

In this experiment each of the four scenarios required the use of different robotic assets.

Scenario A: One Semiautonomous Arial Vehicle (UAV)

Scenario B: One Semiautonomous Ground Vehicle (UGV)

Scenario C: One Tele-operated Ground Vehicle (Tele-op)

Scenario D: One of each of the above vehicles

Display Conditions

In addition to the different asset conditions, display conditions were manipulated across groups. For one group (Latency), there was a latency imposed between control inputs and observable responses of the teleoperated vehicle. To simulate degraded visuals (i.e., reduced bandwidth) a fixed latency of 250 ms was employed based on findings from the literature that latencies between 225-300 ms would degrade human performance in tasks such as teleoperation, tracking, and target acquisition (MacKenzie & Ware, 1993; Held, 1966, cited in Lane et al., 2002; Warrick, 1969, cited in Lane et al., 2002).

For the second group (Frame Rate), the frame rate of the sensor feed video sent to the OCU from the robotic platform was manipulated. In a real situation, available bandwidth would be expected to impact frame rate. Thus an algorithm was employed that decreased frame rate as a function of the distance between the robotic platform and the OCU, to examine the effect of decreasing frame rate on performance. In other words, at the beginning of each scenario, the frame rate would be normal and it would degrade over time (typically about 5 fps at the end of the scenario).

Procedure

Fifteen participants were randomly assigned to either the Latency or Frame Rate group. The order of presentation of the single-robot conditions was counterbalanced, while the 3-robot condition was always the last. The experiment was conducted in two days one week apart. Prior to the start of training on the first day, each participant read and signed an informed consent form and filled out a demographic survey. Then each participant was given briefings on the trainer and route reconnaissance. Following the orientation each participant conducted three thirty minute training trials with discussions between each trial. This concluded the first session. Seven days later participants returned and conducted one additional mission to test their level of training, if the performance level was not adequate they were given re-training. During either the first day or at the start of the second each participant was administered the cube rotation test. Prior to the start of experimentation each participant was read directions from a script, explaining the mission and assets to be used for the particular scenario. The participant was told to begin and given thirty minutes to complete the mission. At thirty minutes or when the participant announced that they were finished, whichever was sooner, the clock was stopped and the participant was administered workload and simulator sickness questionnaires. The next scenario was loaded and the process was repeated until the participant completed four scenarios.

Experimental Design

The experimental design was a randomized block design comparing 2 factors (Latency and Frame Rate) across 4(routes) X 4 (asset mixes). A one–way ANOVA of three dependent performance measures was conducted to compare these factors.

Dependent Measures

The four dependent performance measures were time to complete the given mission, number of distinct targets lazed, and number of appropriate reports (contact and location) sent. The timed measure contained not only the total time but also intermediate times to complete subordinate tasks. Similarly error rates were not confined to target identification but also completion of additional tasks and attention to mandatory signals. Specific dependent measures included the following:

Time to complete mission: A real number in seconds that states the total time to complete the mission.

Number of Targets Lazed: A percent value that represents the number of distinct enemy targets the participant lazed out of the total possible enemy targets (12).

Time to Correct Commo Fault: A real number in seconds that represents amount of time participants took to recognize and correct a system fault.

Number of Contact Reports: A percent value that represents the number of contact reports the participant made; should equal the number of enemy targets lazed.

Number of Location Reports: An integer number that represents the number of location reports made during the scenario.

Workload Questionnaire: Integer numbers that represent the self-reported scores in ten areas.

CHAPTER FOUR
RESULTS

Spatial Ability

The mean for the cube rotation test was 10.17 (S.D.= 4.47), with a median of 11. For any analysis using spatial ability the participants were split about the median, with those scoring 11 or better designated as "high spatial" and those scoring below 11 as "low spatial".

Workload

Participants' self-assessment of workload was significantly affected by Asset condition, $F(3, 54) = 6.437$, $p < .005$. The perceived workload was higher in the Mixed condition (M = 72.3, S.D. = 14.99) compared to the single asset conditions (M = 60.9 [S.D. = 16.64], M = 61.0 [S.D. = 15.04], M = 64.6 [S.D. = 13.27] for Teleop, UAV, and UGV conditions, respectively).

Simulator Sickness

The Total Severity Score of the SSQ was computed for each participant. Participants rated their simulator sickness as the most severe in the Mixed condition and the least severe in the UAV condition. None of the main effects were significant.

Completion

The following figures display the number of participants that completed the scenarios within the 30 minute time limit.

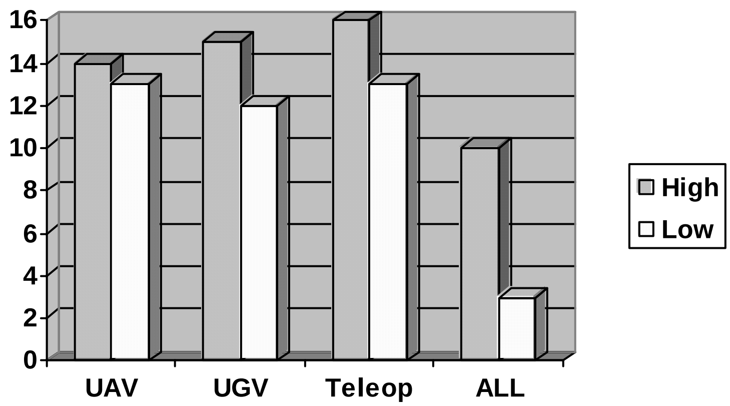

Figure 2
Completed scenarios by robotic asset condition and spatial ability (high vs. low)

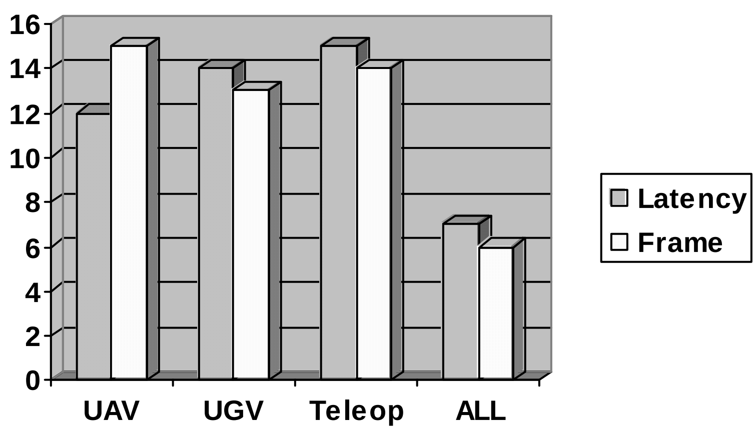

Figure 3
Scenarios by robotic asset condition and video condition (latency vs. frame)

Condition Statistics (Latency vs. Frame)

The following two tables (2 and 3) display results for the scenario in which the participants operated all three assets simultaneously. For the analysis, participants that did not complete the scenario in the 30 minute time limit are excluded.

Table 2
Descriptive Statistics for Mixed Asset Scenario vs. Video Condition

Measure	Condition	N	Mean	Std Dev
Total Time	Frame	6	1540.542	229.239
	Latency	7	1510.881	223.182
Commo Fault	Frame	6	5.261	6.101
	Latency	7	10.467	13.185
Total Targets	Frame	6	9.83	1.472
	Latency	7	8.43	2.992
Contact Reports	Frame	6	11.17	1.472
	Latency	7	11.00	4.830
Location Reports	Frame	6	21.83	8.183
	Latency	7	17.86	3.805

Table 3
ANOVA for Mixed Asset Scenario vs. Video Condition

Asset	Measure	Sum of Squares	df	Mean Square	F	Sig.
Total Time	Between groups	2842.204	1	2842.204	.056	.818
	Within Groups	561616.284	11	51056.026		
	Total	564458.488	12			
Commo Fault	Between groups	87.597	1	87.597	.784	.395
	Within Groups	1229.339	11	111.758		
	Total	1316.936	12			
Total Targets	Between groups	6.375	1	6.375	1.086	.320
	Within Groups	64.548	11	5.868		
	Total	70.923	12			
Contact Reports	Between groups	.090	1	.090	.007	.937
	Within Groups	150.833	11	13.712		
	Total	150.923	12			
Location Reports	Between groups	51.079	1	51.079	1.332	.273
	Within Groups	421.690	11	38.335		
	Total	472.769	12			

Spatial Ability Statistics

The following tables (4-11) display the descriptive statistics and ANOVA results for the individual dependent variables vs. spatial ability. In all of the analysis the participants that did not complete the given scenario within the 30 minute time limit are excluded.

Table 4 displays the descriptive statistics for total mission time vs. spatial ability (high or low).

Table 4
Descriptive Statistics: Total Time vs. Spatial Ability

Asset	Spatial Ability	N	Mean	Std Dev
UAV	Low	13	1601.739	244.577
	High	14	1232.421	261.648
UGV	Low	12	1553.070	255.092
	High	15	1401.330	316.703
Teleop	Low	13	1292.044	293.304
	High	16	998.133	283.154
All	Low	3	1581.253	251.138
	High	10	1507.566	217.507

Table 5 displays the results for the one-way ANOVA for total mission time vs. spatial ability (high or low).

Table 5
ANOVA for Total Time vs. Spatial Ability

Asset	**Measure**	**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**
UAV	Between groups	919409.775	1	919409.775	14.296	.001
	Within Groups	1607793.774	25	64311.751		
	Total	2517203.548	26			
UGV	Between groups	153500.521	1	153500.521	1.810	.191
	Within Groups	2120012.407	25	84800.496		
	Total	2273512.929	26			
Teleop	Between groups	619581.090	1	619581.090	7.485	.011
	Within Groups	2234980.390	27	82777.051		
	Total	2854561.480	28			
ALL	Between groups	12530.361	1	12530.361	.250	.627
	Within Groups	551928.127	11	50175.284		
	Total	564458.488	12			

Table 6 displays the descriptive statistics for total number or targets lazed vs. spatial ability (high or low).

Table 6
Descriptive Statistics Total Targets Lazed vs. Spatial Ability

Asset	Spatial Ability	N	Mean	Std Dev
UAV	Low	13	9.69	2.496
	High	14	10.86	1.351
UGV	Low	12	9.17	1.115
	High	15	9.80	1.146
Teleop	Low	13	5.38	2.142
	High	16	4.63	1.996
All	Low	3	8.0	5.196
	High	10	9.4	1.174

Table 7 displays the results for the one-way ANOVA for total number of targets lazed vs. spatial ability (high or low).

Table 7
ANOVA for Total Targets Lazed vs. Spatial Ability

Asset	**Measure**	**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**
UAV	Between groups	15.238	1	15.238	4.125	.052
	Within Groups	103.429	28	3.694		
	Total	118.667	29			
UGV	Between groups	2.674	1	2.674	2.085	.161
	Within Groups	32.067	25	1.283		
	Total	34.741	26			
Teleop	Between groups	4.139	1	4.139	.973	.333
	Within Groups	114.827	27	4.253		
	Total	118.966	28			
ALL	Between groups	4.523	1	4.523	.749	.405
	Within Groups	66.400	11	6.036		
	Total	70.923	12			

Table 8 displays the descriptive statistics for the total number of contact reports vs. spatial ability (high or low).

Table 8
Descriptive Statistics Contact Reports vs. Spatial Ability

Asset	Spatial Ability	N	Mean	Std Dev
UAV	Low	13	11.31	3.250
	High	14	11.36	2.134
UGV	Low	12	9.67	1.303
	High	15	10.07	2.434
Teleop	Low	13	8.62	2.755
	High	16	8.31	4.571
All	Low	3	8.67	5.859
	High	10	11.80	2.573

Table 9 displays the results for the one-way ANOVA for total number of contact reports vs. spatial ability (high or low).

Table 9
ANOVA for Contact Reports vs. Spatial Ability

Asset	**Measure**	**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**
UAV	Between groups	.016	1	.016	.002	.963
	Within Groups	185.984	25	7.439		
	Total	186.000	26			
UGV	Between groups	1.067	1	1.067	.262	.613
	Within Groups	101.600	25	4.064		
	Total	102.667	26			
Teleop	Between groups	.658	1	.658	.044	.836
	Within Groups	404.514	27	14.982		
	Total	405.172	28			
ALL	Between groups	22.656	1	22.656	1.943	.191
	Within Groups	128.267	11	11.661		
	Total	150.923	12			

Table 10 displays the descriptive statistics for the total number of location reports vs. spatial ability (high or low).

Table 10
Descriptive Statistics Location Reports vs. Spatial Ability

Asset	Spatial Ability	N	Mean	Std Dev
UAV	Low	13	6.46	2.222
	High	14	9.21	3.577
UGV	Low	12	7.67	3.143
	High	15	9.67	4.100
Teleop	Low	13	7.54	2.025
	High	16	10.06	3.750
All	Low	3	14.33	6.658
	High	10	21.30	5.498

Table 11 displays the results for the one-way ANOVA for total number of location reports vs. spatial ability (high or low).

Table 11
ANOVA for Location Reports vs. Spatial Ability

Asset	**Measure**	**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**
UAV	Between groups	51.079	1	51.079	5.661	.025
	Within Groups	225.588	25	9.024		
	Total	276.667	26			
UGV	Between groups	26.667	1	26.667	1.938	.176
	Within Groups	344.00	25	13.760		
	Total	370.667	26			
Teleop	Between groups	45.694	1	45.694	4.742	.038
	Within Groups	260.168	27	9.636		
	Total	305.862	28			
ALL	Between groups	112.003	1	112.003	3.415	.092
	Within Groups	360.767	11	32.797		
	Total	472.769	12			

CHAPTER FIVE
DISCUSSION

Overview

The objective of this study was to offer alternatives for improving human performance in the operation of multiple robotic assets within the current battlefield limitations. Proposed possibilities include managing an operator's workload within the confines of current limited bandwidth and screening possible operator's for inherent spatial ability. The results indicate that judicious allocation of workload, capitalizing on the inherent differences in robot types appears to have potential for improving performance. They also indicate that spatial ability is a strong predictor for operator performance and screening potential operators for high spatial ability should yield improved results. Although few of the statistics are significant the trends suggest that a refined study may prove more telling.

Of the four scenarios, the one in which the participants had to operate all three robots was the hardest. This is confirmed in the workload questionnaire $F(3, 54) = 6.437$, $p < .005$, and the percent of participants that completed the scenarios; 43% for the mixed scenario and above 90% for the other three. These results support what is known about HIP and performance; there are bottlenecks in the way humans process information and these bottlenecks can lead to limitations in performance (Wickens & Hollands, 2000). This supports the belief that in terms of system design, the focus of this study should be on the multitasking scenario because this is where the performance degradation will likely manifest if a system is not systematically designed to manage workload.

First Hypothesis

Although there was no statistically significant findings when analyzing the mixed asset scenario by condition (p values all greater than .2), four of the five variables (i.e., number of commo faults detected, total targets lazed, contact reports made, and location reports made) suggest that performance during a frame delayed condition may have some advantages (see Figure 4). Total time was the only performance outcome that was not in the expected direction. A power analysis revealed that for three of the variables, increasing the sample size to as few as 33 participants may potentially yield significant results (see Table 12). These results suggest that there may be some benefit to degrading the visual-spatial information flow associated with semi-autonomous vehicles, thereby reducing visual-spatial workload, and only drawing attention to such assets at critical times. (Note: While this study used a visual cue to draw attention to the semi-autonomous vehicle, future research should consider drawing attention via an auditory alert, as this would likely glean working memory benefits based on Wickens' (1991) MRT). Beyond its potential human performance benefits, this solution supports the computational bandwidth limitations of net-centric warfare. This benefit is not to be overlooked, as the management of bandwidth has two important military implications. First, less data transmission reduces the opportunity for enemy interception. Second, managing the bandwidth may prevent loss transmissions that could result in misunderstood commands and other battlefield awareness concerns.

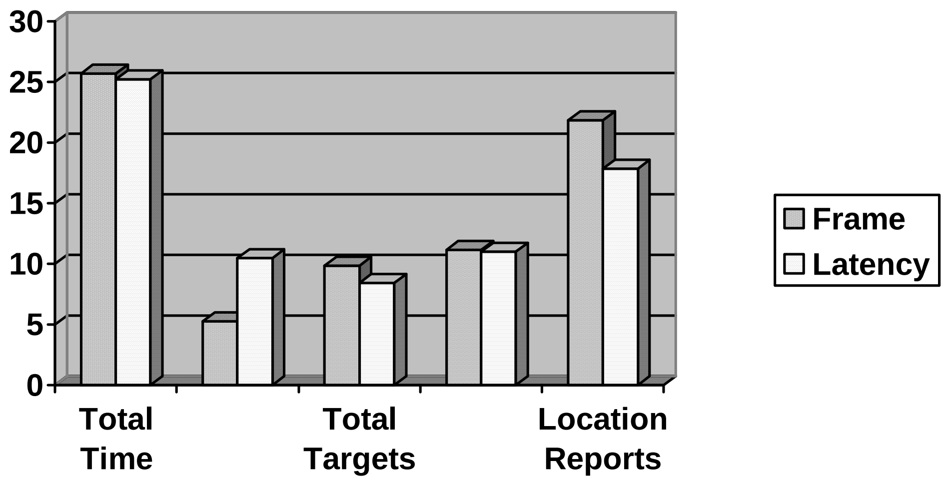

Figure 4
Mean results Mixed Asset vs. Video Condition

Table 12
Sample size after power analysis

	Commo Fault	Total Targets	Location Reports
Original Sig.	.395	.320	.273
Sample	33	25	21

Second Hypothesis

As predicted, individuals with high spatial ability had better total times, especially in the UAV scenario, $F(1, 25) = 14.296$, $p = .001$. The high spatial group was 30% faster, on average, than the low spatial group in operating the UAV. The total time performance for the UGV and Teleoperated scenarios were both better for high spatial individuals, the Teleop was significantly better, $F(1, 27) = 7.485$, $p < .05$, while the UGV approached significance , $F(1, 27) = 1.810$, $p = .19$. The high spatial group was 24% faster, on average, than the low spatial group in operating the Telop and 11% faster, on average, operating the UGV. These results support current research that suggests teleoperating a vehicle is difficult and that high spatial individuals will perform these tasks better (Lathan & Tracey, 2002). They also suggest that UAV may pose a greater challenge to low spatial individuals than other forms of robotic assets, which may be due to its operation in a 3-D space as opposed to the two-dimensional space traversed by ground vehicles. The time results for the mixed asset scenario were not significant, but with 10 of the 13 participants that completed this scenario being high spatial, there is a trend in favor of the high spatial group that should be further investigated.

In the UAV only scenario three of the four dependent variables were significantly better for high spatial individuals (highlighted in Table 13).

Table 13
UAV scenario vs. Spatial Ability

Variable	F	Sig.
Total Time	14.296	.001
Total Targets	4.125	.05
Contact Reports	.002	.96
Location Reports	5.661	.025

The results for the remaining scenarios (i.e., UGV and teleoperated) are similar and demonstrate that operators with higher spatial ability will likely perform better than lower spatial ability operators and confirms the importance of spatial ability in selecting operators. In terms of performance, the high spatial group, on average, lazed 12% more targets than the low spatial group when operating the UAV. The high spatial group also made, on average, 43% more location reports than the low spatial group when operating the UAV and 33% more, on average, when operating the teleoperated robot. These results further support the position that spatial ability has significant performance implications when operating robotic assets, particularly UAVs. It is recommended that spatial ability be used as a screener for selection of military robotic operators, particularly if they are to operate UAVs.

CHAPTER SIX
CONCLUSION

The United States Army is intent on developing and fielding an array of robotic assets. The wide spread fielding of these assets coupled with the reduction in manning will result in a single operator managing several robotic assets. This study has shown that multitasking in its current form is very difficult and will generally yield reduced performance. The military must manage workload, not tax an already crowded bandwidth and capitalize on individual abilities to be successful.

Critical thought must be applied to managing operator workload so as to not overload the operator during multitasking. Leveraging multiple HIP processing resources or systematically limiting data input are possible alternatives. This study provides data that suggest there may be some benefit to the latter approach. Specifically, by degrading the visual-spatial information flow associated with semi-autonomous vehicles, which do not require constant monitoring, the overall visual-spatial workload during multitasking of multiple robotic assets may be reduced. Attention could then be drawn to such assets only at critical times (e.g., target identification, location reporting) via an alert or other mechanism. Beyond its potential human performance benefits, this solution supports the computational bandwidth limitations of net-centric warfare. Operational security and a higher probability of consistent complete data transmission are two additional byproducts of a judiciously managed bandwidth.

In selecting personnel the results of this study indicate that the military should leverage individual abilities to target recruiting of potential operators that have critical skills for managing robotic assets. This study supports the current research in clearly identifying an individual's spatial ability as a key indicator of improved performance, particularly when operating aerial vehicles. The innate spatial ability to translate information from multiple assets, offering different views of the battlefield, has the potential to greatly enhance an operator's performance. Screening for this ability is thus strongly recommended.

CHAPTER SEVEN
FUTURE RESEARCH

To move the research in this area forward two immediate areas of future research are recommended. First, the positive trend seen in the effects of video frame delay should be investigated further. A robust design that focuses on the effects of frame delay on multitasking scenarios utilizing a larger sample may yield more significant results. The overall objective should be to examine the effects of existing battlefield conditions (e.g., limited bandwidth), as well as task requirements, in an effort to design systems that overcome negative effects (e.g., of limited bandwidth) by judiciously managing information flow and associated operator workload.

Second, an alternative study could look at the use of multi-modal information flow (MRT) to manage operator workload during multitasking. Although currently bandwidth limited, the eventual possibility for improved data transmission may make possible the use of audio and haptic channels on the battlefield. Current research is clear on the positive implications of leveraging additional HIP resources and future research should investigate the implementation of these resources to multitasking on the battlefield.

Future military systems will likely increase in complexity so any research that investigates the human implications of this complexity should yield positive results.

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