Management of Multiple Dynamic Human Supervisory Control Tasks for UAVs

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Abstract

Network-centric operations, in which multiple human and computer-based agents are linked in order to leverage information superiority, will bring increases in available information sources, volume of information and operational tempo, all of which will place higher cognitive demands on operators. This is an especially critical problem for operators who will be attempting to control multiple vehicles, which could be ground, air, or underwater-based. This paper will illustrate that when modeling the number of vehicles a single operator can control, it is important to model the sources of wait times, especially since these times could potentially lead to system failure. Specifically, these sources of vehicle wait times include interaction wait time, queues for multiple vehicles, and loss of situation awareness. In addition, it is critical to incorporate wait times that are incurred as a function of switching costs between tasks. The conflict between focusing on primary tasks, monitoring for alerts, and switching attention to emergent tasks is a fundamental problem for operators attempting to supervise multiple robots or autonomous vehicles. With the primary focus on the concept of wait times, this paper will discuss recent efforts to model operator capacity for management of multiple vehicles, outline a basic framework for modeling wait time, and discuss how these elements relate to the ability of a human to control multiple UAVs.

1 Introduction

The concept of network-centric operations, in which multiple human and computer-based agents are linked in order to leverage information superiority, is popular in the military command and control arena, but also can be found in other human supervisory control domains such as air traffic control and first-response team management. Human supervisory control (HSC) occurs when a human operator monitors a complex system and intermittently executes some level of control on the system though some automated agent. In future network-centric operations, it is likely that operators will manage multiple supervisory tasks at once, as HSC tasks are primarily cognitive in nature and generally do not require constant attention and/or control. For example, a single air traffic controller can handle multiple aircraft because the onboard pilots handle the flying task, while the controller is primarily concerned with navigation tasks that do not require constant attention. Similarly, while many operators are presently needed to control a single unmanned aerial vehicle (UAV), as technology and autonomous control improve, automation will handle the task of flying, thus enabling the individual controller to control a greater number of UAVs.

However, the primary advantage of network-centric operations, that of rapid access to information across the network, will likely be a major bottleneck and point of failure for those humans who must synthesize data from the network and execute decisions in real-time, often with high-risk consequences under significant uncertainty. Network-centric operations will bring increases in the number of available information sources, volume of information and operational tempo, all which place higher cognitive demands on operators. In time-pressured scenarios like those expected in command and control, efficiently allocating attention between a set of dynamic tasks becomes critical to both human and system performance. In the future vision of allowing a single operator to control multiple unmanned vehicles (which could be on land, in the air, or under water), it is not well understood how operators will manage multiple vehicles, what kind of decision support will aid or hinder the operator, and how human cognitive limitations will impact overall system effectiveness. To this end, this paper will discuss recent efforts to model human capacity for management of multiple vehicles, outline a basic framework for modeling wait time, and how these elements relate to the ability of a human to control multiple UAVs.

2 Background

In an attempt to model human-robot (ground-based) interaction, it has been proposed that the number of robots a single individual could control can be represented by equation 1 (Goodrich, Quigley, & Cosenzo, 2005; Olsen & Goodrich, 2003; Olsen & Wood, 2004) In this equation, FO (Fan Out) equals the number of robots a human can effectively control, NT (Neglect Time) is the expected amount of time that a robot can be ignored before its performance drops below some threshold, and IT (Interaction Time) is the time it takes for a human to interact with the robot. The addition of one in equation 1 represents the baseline condition in that an operator can control a single robot. While originally intended for ground-based robots, this work has direct relevance in the UAV community as these systems are becoming more autonomous and will move from the manual control domain to that of multiple vehicle supervisory control.

$$FO = \frac{NT}{IT} + 1 \qquad \textbf{Eqn. 1}$$

Modeling interaction and neglect time are critical for understanding human workload in terms of overall management capacity, but there remains an additional critical variable that must be considered when modeling human control of multiple robots, regardless of whether they are on the ground or in the air, and that is the concept of Wait Time (WT). In HSC tasks, humans are serial processors in that they can only solve a single problem or task at a time (Chapanis et al., 1951), and while they can rapidly switch between tasks, any sequence of tasks requiring complex cognition will form a queue and consequently wait times will build. In the context of a system of multiple vehicles or robots in which two or more vehicles will likely require attention simultaneously from a human operator, wait times are significant in that as WT increases, the actual number of vehicles that can be effectively controlled decreases. Figure 1 illustrates how wait times could impact an overall system. In multiple vehicle supervisory control, operators interact with a robot to bring its performance to some acceptable performance threshold and then neglect it until such time that it requires assistance. Point A in figure 1 represents a discrete event that causes the robot to require operator assistance such as system failure or the need for clarification of a goal state. The robot must wait while the human recognizes the problem, solves the problem internally, and then communicates that goal to bring the robot to another acceptable state.

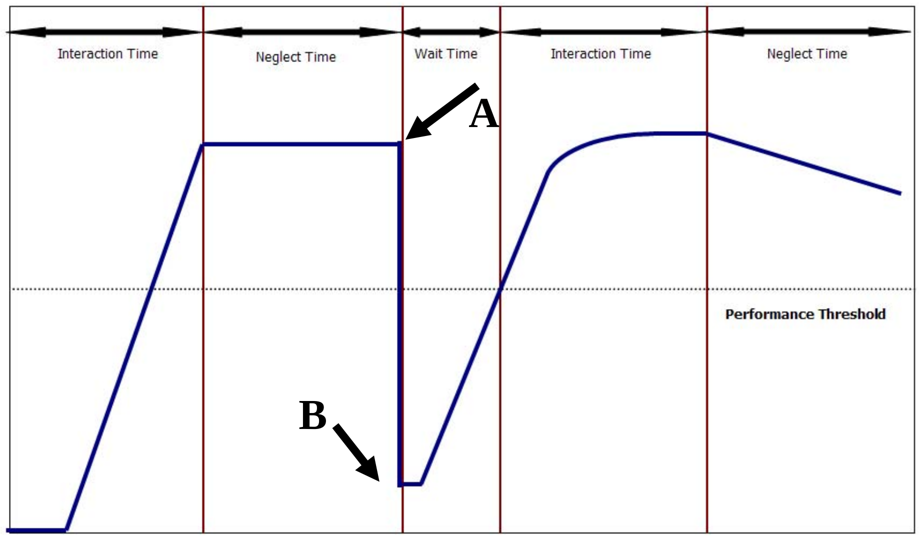

Figure 1: The relationship between interaction, neglect, and wait times

While interaction and neglect times are all important in predicting human capabilities for handling multiple robots, for those domains that are time-critical and high risk like UAVs, WT becomes a critical point for possible system failure. In many ground-based robot applications such as mine-sweeping, waiting for human interaction may not critical, but certainly for UAVs and UUVs (unmanned underwater vehicles) with expected time on targets and dynamic threat areas, waiting is not only sub-optimal, it can be extremely hazardous. However, even ground-based robots (or unmanned ground vehicles, UGVs) engage in time-critical missions such as search and rescue which would be negatively impacted if the problem of WT was not addressed. While most robots and vehicles can be preprogrammed to follow some predetermined contingency plan if they do not receive required attention, mission success will likely be significantly degraded if wait times grow unexpectedly.

2.1 Wait Times

From the robot or vehicle perspective, WT imposed by human interaction (or lack thereof) can be decomposed into three basic components: 1) wait time in the human decision-making queue (WTQ), 2) interaction wait time (WTI), and 3) wait time due to loss of situation awareness (WTSA). For example, suppose an operator is controlling two robots on a semi-autonomous navigation task (much like the Mars Rovers). While typical operations involve human interaction with a single vehicle, there will be times when both vehicles require attention simultaneously or near-simultaneously. When this occurs, if the human operator begins assisting the first robot immediately, the first robot must wait while the operator solves the problem and then issues the commands to it (WTI_1). For the second robot, the time it waits in the queue (WTQ_2) is effectively WTI_1.

IT, which was previously defined as the time it takes for a human to interact with a robot, can be further decomposed. IT is the time during which a human's attention is focused on a single robot in order to solve a problem or induce some change to improve performance above a specified threshold. From the human perspective, IT includes the time required to determine the nature of the problem, solve the problem, and communicate that solution to the robot, with some type of feedback. Thus the robot must wait some period of time during the "interaction" due to the human decision-making process. In teleoperation where the human is directly controlling a robot's movements and positions, interaction wait times might be very small, and occur in rapid succession as the controller gets sensor feedback and adjust commands accordingly. However, in other scenarios that require minimal manual control but significant cognitive input such as the need to provide a new mission to a UAV, WTI can be quite large depending on the complexity of the problem. Previous research has indicated that system interaction times of operators should not exceed 0.7 of the total system operating time due to cognitive and physical limitations (Rouse, 1983; Schmidt, 1978). For the remaining discussion in this paper, WTI will be considered to be subsumed in IT, which includes time needed for the human and robot to make decisions and time for communications between the two.

$$WT = \sum_{i=1}^{X} WTQ_i + \sum_{j=1}^{Y} WTSA_j \qquad FO = \frac{NT}{IT(WTI) + WT}$$ **Eqn. 3 & 4**

- WTQ: Queuing wait time
- WTSA: Wait time caused by a loss of situation awareness
- WTI: Wait time due to human decision making, nested in overall interaction time
- X = number of interaction queues that build
- Y = number of time periods in which a loss of SA causes wait time

WTSA is perhaps the most difficult wait time component to model because it represents how cognitively engaged an operator is in the task. Situation awareness (SA) is generally defined as having three levels, which are: 1) the perception of the elements in the environment, 2) the comprehension of the current situation, and 3) the projection of future status" (Endsley, 1988; Endsley, 1995). While SA can decrease under high workload due to competition for attentional resources (Wickens, 1995), it can also decrease under low workload due to boredom and complacency (Rodgers, Mogford, & Strauch, 2000). Human error is an unfortunate element of any HSC system and in the context of developing a wait time model, it is likely that in addition to all the other known sources of WT, loss of SA will cause wait times. If an operator does not realize a robot or vehicle needs attention, the time from the initial onset of the event to actual operator intervention could range from seconds to minutes. While notifications and critiquing devices included in decision support systems can help to alleviate added wait time due to loss of SA, it is still an event that at the very least, should be included as a probabilistic model in a larger model of wait time for human interaction with multiple vehicles. Equation 3 categorizes general wait time that is not part of human-robot interaction as the wait times that result from queues due to near-simultaneous arrival of problems plus the wait times due to the operator loss of SA. Equation 4 demonstrates how the Fan Out equation would change as a result of the inclusion of wait times.

3 The Impact of Wait Times: A Case Study

Cummings and Guerlain (2004) have also attempted to quantify how many unmanned, semi-autonomous vehicles a single operator can control in the domain of land attack missile control, specifically for the Navy's new Tactical Tomahawk missile. Due to new GPS retargeting capabilities, Tactical Tomahawk missiles, previously fire-and-forget, can now take on missions similar to that of UAVs in that their flight paths can be changed in-flight to emergent, time critical targets. As part of this new capability, Tactical Tomahawk missiles could be stationed in loiter patterns to await further orders, much like what is envisioned for both surveillance and combat UAVs.

Human supervisory control of Tactical Tomahawk missiles generally encompasses two primary subtasks: 1) monitoring the missiles in-flight, which requires tracking missile progress both in time and distance as well as monitoring subsystem integrity such as navigation and communications (using equation 1, this monitoring time is equivalent to NT), and 2) retargeting missiles when an emergent situation occurs. Emergent situations, for example, can include the appearance of a mobile surface-to-air missile site or a missile system failure that requires redirection of an additional in-flight missile to cover a high priority target. This time to retarget is essentially interaction time (IT).

The goal of the initial Tactical Tomahawk human-in-the-loop study was to develop a predictive model that could aid in the determination of how many missiles an individual operator could control, given varying workload levels and increasing complexity of scenarios. Results revealed that when given 8, 12, and 16 missiles to monitor and possibly retarget, subjects were able to effectively handle 8 and 12, but experienced significant degradation in performance at 16 missiles (Cummings & Guerlain, 2004). These workload predictions are very similar to those of air traffic controllers (Hilburn, Bakker, Pekela, & Parasuraman, 1997), so in situations where controllers are interacting with semi-autonomous vehicles that only require interaction in terms of setting new goal states, beyond 12 vehicles potentially presents a cognitive saturation state.

While the initial Tomahawk research was not focused on wait times per se, re-evaluation of the data in terms of the WT framework proposed above can provide insight for future UAV, UGV, and UUV studies. Forty-two subjects, all naval personnel either active duty or retired and all with Tomahawk domain expertise, participated in this study. After extensive practice, subjects completed two counterbalanced test scenarios, one under low workload conditions (emergent scenarios arrived every four minutes) and one under high workload (emergent scenarios arrived every two minutes). In each session subjects always controlled the same number of missiles (either 8, 12, 16), thus the missile factor was between-subjects, while the workload factor was within-subjects. The statistical model used was a repeated measures, linear mixed model.

In order to investigate the impact of the independent variables on the WTI and WTQ components, two scenarios were investigated, that of the arrival of a single emergent target and that of dual emergent targets. These scenarios can be compared to a single robot/vehicle that demands attention as compared to two vehicles that require attention because when a target emerged, it required a single missile. When the single target emerged, the operator had to select a single missile to prosecute that target from the group of missiles allocated to them. The dual scenario condition was very similar to the single condition, but two emergent targets arrived near-simultaneously, 5 seconds apart, and were virtually identical to the single scenario, but each requiring a different missile. Figure 2 demonstrates that across all missile categories in the single emergent target scenario, WTI_1 was fairly consistent, meaning the missile to be retargeted had to wait ~20 seconds before the decision was made. However in the dual emergent target scenario, the wait time for the second missile, WTI_2 was significantly affected by the increase in workload due to the missile category,

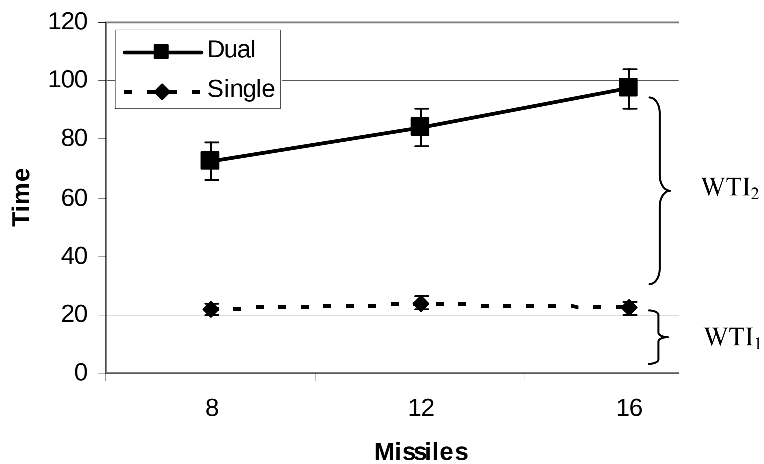

Figure 2: Wait Times for Single vs. Dual Vehicle Interaction

confirmed statistically through a significant interaction between missiles and scenarios (($F(4, 130) = 3.19$, $p = .016$, $\alpha = .05$). Recall that for the second vehicle needing human intervention, the human interaction with the first represents the queuing wait time for the second (WTQ_2).

These results demonstrate that as the number of vehicles that required immediate attention increased, wait times increased, and not simply in an additive fashion. If a single scenario took on average 20 seconds to solve, then theoretically, if two scenarios arrived together, then the total time of solution for both should fall somewhere around 40 seconds, two times the baseline solution time. Yet it is clear that wait times increased 3 – 5 times greater than the baseline condition with the addition of a dual emergent target scenario, and WTI_2 significantly increased as subjects had more missiles to consider as solutions. These experimental results are evidence of a concept known as "switching costs", in which switching between tasks incurs added cost in terms of wait time because of the cognitive need to orient to the new problem. Switching costs are not incurred simply as a function of change detection but occur as an operator regains the correct mental model and situation awareness needed to solve the new problem. In figure 1, the concept of a switching cost is illustrated in point B, in which vehicle performance cannot begin to be improved until the human is oriented to the new problem. Thus the term of interaction wait time (WTI) also contains a component of WTSC (wait time due to switching cost).

While the concept of a switch cost is relatively new to the human-robot interaction community (Goodrich et al., 2005), it is a recognized issue in human supervisory control domains such as command and control, air traffic control, and the monitoring of process control displays. Switching costs routinely occur because operators spend time monitoring unfolding events, but they also periodically engage in interactive control tasks such as giving aircraft instructions or raising a fluid level in a tank. When task engagement occurs, operators must both concentrate attention on the primary task, but also be prepared for alerts for external events. This need to concentrate on a task, yet maintain a level of attention for alerts causes operators to have a conflict in mental information processing. Concentration on a task requires task-driven processing which is likely to cause decreased sensitivity or attention to external events. Interrupt-driven processing, needed for monitoring alerts, occurs when people are sensitized to possible problems and expect distraction. While interrupt and task driven processing can both be present in a person, attention must be shared between the two and switching can incur cognitive costs that can potentially result in errors (Miyata & Norman, 1986). In addition, Gopher et al. (1996) demonstrated that not only is there a measurable cost in response time and decision accuracy when switching attention between tasks, but costs are also incurred by the mere consideration of switching tasks. The conflict between focusing on tasks, monitoring for alerts, and switching attention to emergent tasks is a fundamental problem for operators attempting to supervise a complex system such as multi-robots or autonomous vehicles.

In the case of the Tomahawk multiple missile control case, it is evident that wait times increased significantly beyond what was expected in the case of managing two missiles instead of one, and this increase is likely due to switching costs. However, it is important to evaluate this increase in light of overall system performance since the bottom line is whether or not human can effectively handle multiple vehicles, not specifically how long it took them to make a decision. When the decision times, workload, and missile levels were included in a backwards regression model to predict overall system performance, the missile level was removed and only workload and decision times were significant predictors in the model (partial correlations: Decision time = -0.474, Workload = 0.267). The increase in decision time and thus vehicle wait time was the most significant contributor to system performance and as wait times increased, overall performance decreased.

4 Implications for Management of Multiple UAVs

The Tactical Tomahawk research is helpful in identifying problem areas in regards to wait times and switching costs, but since the experiment was not originally designed to examine these issues, the results are of limited value. What is needed for the UAV community is a comprehensive study into the problem of wait times, to include their impact on overall system performance, how to account for them more accurately in a workload prediction model, and how to identify and perhaps model the WT individual components, especially that of WTSA. Another significant area of inquiry that is needed is the impact of increasing levels of automation on decision support, wait times, and overall system performance.

Levels of automation (LOAs), highly relevant to decision support systems such as those that will aid controllers of multiple robots or vehicles, range from fully automated where the operator is completely left out of the decision process to minimal levels where the automation only makes recommendations or simply provides filtering mechanisms. These levels are represented in Table 1 (Sheridan & Verplank, 1978; Wickens, Mavor, Parasuraman, & McGee, 1998). For rigid tasks that require no flexibility in decision-making and with a low probability of system failure, higher levels of automation often provides the best solution (Endsley & Kaber, 1999). A "black box" approach to full automation, in which the automation's decision making is completely transparent to the human, can be useful for redundant tasks that require no knowledge-based judgments such as autopilot systems. However, even partially automated systems can result in measurable costs in human performance, such as loss of situational awareness, complacency, skill degradation, and decision biases (Parasuraman, Sheridan, & Wickens, 2000).

Table 1: Levels of Automation

Automation Level	Automation Description
1	The computer offers no assistance: human must take all decision and actions.
2	The computer offers a complete set of decision/action alternatives, or
3	narrows the selection down to a few, or
4	suggests one alternative, and
5	executes that suggestion if the human approves, or
6	allows the human a restricted time to veto before automatic execution, or
7	executes automatically, then necessarily informs humans, and
8	informs the human only if asked, or
9	informs the human only if it, the computer, decides to.
10	The computer decides everything and acts autonomously, ignoring the human.

In the context of managing multiple UAVs, increasing the levels of automation will reduce workload, wait times, and, superficially, switching costs, but there are several measurable costs for both operators and the system in general. Loss of situation awareness and the propensity for automation bias are significant problems that can result when automation authority increases, and the impact of increasing levels of automation on switching costs has not been studied. Significant wait times due to human cognitive capacity limits could become a critical failure point which can be alleviated to some degree by increasing the automation authority. However, higher levels of automation could also be a source of significant human and system error. The next phase of this research project will address the problems of identifying and measuring the components of wait time, and evaluate how increasing levels of automation influence both individual operator performance as well as overall system performance.

5 Conclusions

The ability for a single operator to effectively control multiple agents such as UAVs, UGVs, and UUVs is a fundamental component of the military's future vision of network-centric warfare. However, if not well understood and accounted for in design strategies, human cognitive limitations could be a significant source of degraded system performance and possible failures. When modeling the number of robots/vehicles a single operator can control, it is important to model the sources of wait times, especially since these times could potentially lead to system failure. Specifically these sources of system/robot wait time include interaction time, queues for multiple vehicles, and loss of situation awareness. As evidenced by previous research in the control of multiple Tomahawk missiles, it is important when modeling multiple human-vehicle interaction not to simply add interaction times from single events. When humans switch between tasks, a cost in the form of additional time is incurred due to the need for cognitive reorientation to the new problem. While this paper outlines general concepts in wait time modeling, more research is needed in the development of wait time and switching costs models, wait time costs incurred by the loss of SA, as well as the impact of increasing levels of automation on wait times and overall system performance.

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