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Effect of Time Pressure and Task Uncertainty on Human Operator Performance and Workload for Autonomous Aerial Vehicle Missions

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EFFECT OF TIME PRESSURE AND TASK UNCERTAINTY ON HUMAN OPERATOR PERFORMANCE AND WORKLOAD FOR AUTONOMOUS AERIAL VEHICLE MISSIONS

by

TREVOR PETERSON
B.S. Colorado State University, 2007

A Thesis Submitted to the Department of Human Factors & Systems in Partial Fulfillment of the Requirements for the Degree of Master of Science in Human Factors and Systems.

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by

Trevor Peterson

This thesis was prepared under the direction of the candidate’s thesis committee chair, Dr. Dahai Liu, Ph.D., Department of Human Factors & Systems, and has been approved by members of the thesis committee. It was submitted to the Department of Human Factors & Systems and has been accepted in partial fulfillment of the requirements for the degree of Master of Science in Human Factors & Systems.

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Abstract

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Unmanned aircraft systems (UAS) are being utilized at an increasing rate for a number of military applications. The potential for their use in the national airspace is also of interest to the Federal Aviation Administration, but there are some concerns about the safety of flying unmanned aircraft. The role of a UAS operator differs from that of a pilot in a manned aircraft, and this new role creates a need for a shift in interface and task design in order to take advantage of the full potential of these systems. This study examined the effect of time pressure and task uncertainty have on autonomous unmanned aerial vehicle operator task performance and workload. Thirty undergraduate students at Embry-Riddle Aeronautical University participated in this study. The primary task was image identification, and secondary tasks consisted of responding to events encountered in typical UAS operations. Time pressure was found to produce a significant difference in subjective workload ratings as well as secondary task performance scores, while task uncertainty was found to produce a significant difference in the primary task performance scores. The results were examined, and recommendations for future research are discussed.
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Introduction

Currently there are over 100 U.S. companies developing more than 300 different Unmanned Aircraft Systems (UAS) designs (FAA, 2009a). Some UASs are able to remain in the air for 30 hours or more because there is no need to land and change pilots. This provides a much more efficient method for accomplishing goals which require long mission times. Not only do current capabilities of UASs allow for the completion of tasks at less cost than current manned aircraft, they also offer the ability to perform tasks that are deemed too dangerous for manned aircraft. The military utilizes UASs to perform these “dull, dirty, and dangerous” missions to avoid the risk of losing human life.

UASs are also on the verge of being utilized within the national airspace. There are currently very few UASs allowed to operate in limited areas, due to uncertainty with the safety related to operating a UAS (AIR-160, 2008). Once these safety concerns are alleviated, the capabilities of UASs can be utilized in a vast number of activities which have not as of yet been discovered. Border patrol, pipeline inspection, crop inspection, law enforcement, and a multitude of applications could be enhanced by the use of UASs in the future. The concerns about UAS safety revolve around the ability of a remotely located pilot to fly in a manner which is safe not only to the aircraft itself, but to everything in the vicinity of the aircraft (Wilson, 2007). There are numerous arguments for research to focus on the differences between manned and unmanned flight with regards to level of safety (DeGarmo & Maroney, 2008; Duke, Vanderpool, & Duke, 2007; Tvaryanas, Thompson, & Constable, 2006).

Accident rates of UASs far exceed those for manned flight. While the idea behind unmanned flight is to avoid the risk to human life, there is still a cost associated with losing a UAS. It is therefore prudent to discover the causes behind the high rate of accidents for UASs, and begin to
provide solutions to some of the issues. Because the military is the largest user of current UAS technology, most of the research has been conducted with military operations in mind. A large amount of this research points to human factors as an area which needs a considerable amount of further study in order to achieve a level of safety equal to that of manned aircraft (Williams, 2004).

Specific human factors issues associated with UASs involve the fact that the human operator has a significantly different role than a pilot in a manned aircraft. This new role requires a shift not only in personnel selected for the job, but the training involved, and an interface design which allows for the optimal cooperation between human and automation in order to achieve the full potential of the system as a whole (Nelson & Bolia, 2006). Research on interface design has opened up new areas of interest, including the control of multiple UASs by one operator. This requires a whole new way of thinking about the implementation of automation and how it affects the operator. The operator of a UAS must be able to monitor not only the state of the aircraft, but that of the aircraft's environment, as well as the control station. This heightens the cognitive demand placed on the operator, and effects on workload are expected. Certain interface designs may be utilized to mediate these effects and the impact of implementing these interfaces is an essential area of research.

Previous research has looked at workload imposed during a multi-UAS controlling task. However, workload effects have been difficult to attain with regards to the number of vehicles being controlled (Liu, Wasson, & Vincenzi, 2008; Reynolds, 2009). This study will focus on using tasks common to the control of UASs to manipulate workload in the operator.
The first area of interest in the current study is the use of UASs for target detection. One of the main roles of UASs in military use today is one of target acquisition. This is made difficult by the technology currently in use, due to low fidelity imaging, inaccuracy of automation in target detection, and uncertainty associated with images (MeCarley & Wickens, 2005). All of these difficulties require the human operator to expend some level of cognitive resources in order to solve them and accurately designate enemy targets. The effect on shifting operator workload has ripple effects on other tasks necessary for the operation of a UAS.

Another area of importance is time pressure effects on the workload of the operator, and any performance detriments they may cause. Current levels of automation can assist the human operator with many tasks, but when the operator’s workload is already high, the assistance of a decision aid, and the time pressure it is associated with, may increase workload and therefore cause performance issues. The relationship between time pressure, workload, and automation is a complex one that has proven difficult to study. Research conducted on UAS operation found that participants rarely utilized the automation, even when time pressure was added and workload was increased (Ruff, Calhoun, Draper, Fontejon, & Guilfoos, 2004).

The current study focuses on the workload imposed on a human operator during a UAS mission task involving varying time pressures and levels of task uncertainty. The study will not only measure workload directly but include measures of performance in order to determine any effects elevated workload may have on performing necessary tasks. In the next section the history of UAS development, as well as current and future uses of UASs, will be reviewed. This is followed by a review of human-automation interaction and the human factors issues associated with it. In particular, this thesis is focused on a review of previous research on target acquisition and time pressure, and their effects on workload.
UAS Development

There is no universal definition for a UAS, and the characteristics of UASs have evolved quite a bit since their inception. The Department of Defense defines a UAS as “A powered, aerial vehicle that does not carry a human operator, uses aerodynamic forces to provide vehicle lift, can fly autonomously or be piloted remotely, can be expendable or recoverable, and can carry a lethal or non-lethal payload”, but the DoD excludes cruise missiles and other forms of ballistic vehicles from their definition (Department of Defense, 2005). The FAA on the other hand, defines UASs as an “Airplane, airship, powered lift, or rotorcraft that operates with the pilot in command off-board, for purposes other than sport or recreation, also known as unmanned aerial vehicle”. The differences in the definition of UASs by these governing bodies can be attributed to the differing roles UASs play for each, as well as the many paths of development UASs have gone through before reaching their current status.

Roles of UASs in the Past

The concept of a pilotless aircraft had its beginnings in the last part of the nineteenth century with an inventor named Nikola Tesla (Newcome, 2004). Tesla was able to give a practical demonstration of wireless control with a torpedo which he marketed to the U.S. Navy. The Navy soon gave up on Tesla’s radio-controlled torpedo, but his demonstration opened the door for other scientists to pursue the same technology in flight. One such scientist was Elmer Sperry who built on Tesla’s ideas by using radio frequencies to control aircraft. The early development of unmanned aircraft was reliant on three crucial technologies: automatic stabilization, remote control, and autonomous navigation. Sperry was the first person to attempt to solve all three problems at once and, with the assistance of his son, was able to demonstrate the ability to
remotely pilot an aircraft over a certain distance and dive at a specified target. Because of the intention to dive at a target, Sperry’s technology was referred to as an “aerial torpedo” (Newcome, 2004). With successful demonstrations to officials in the armed forces, unmanned aircraft sparked interest in military applications and the development of technologies used in unmanned flight were tied directly to the needs of the military.

Sperry’s demonstration of an unmanned aerial torpedo that could be flown into an enemy target peaked the interest of the U.S. military, but the role of unmanned aircraft would soon turn to one of training. On the suggestion of British officials, the U.S. started flying unmanned aircraft as targets used for the training of pilots and anti-aircraft gunners to improve their accuracy and dog-fighting abilities. In the early 1960’s, the idea of using unmanned aircraft as spy planes gained popularity, mostly due to the danger that pilots flying U2 spy planes faced at the time. There were instances of U2 pilots being shot down over hostile territory, which made the need for operating unmanned spy planes all the more evident (Wagner & Sloan, 1992). The cold war spurred on many more advancements in unmanned aircraft, including furthering the abilities of UAVs to perform reconnaissance missions safely, and the ability to carry and deliver lethal payloads. Once weapons are added to the abilities of the system, it is often referred to as an Unmanned Combat Aerial Vehicle (UCAV). A graphical representation of the evolution of UAVs is given in Figure 1.
After the end of the cold war, the United States spends less on defense and is more likely to be involved with peacekeeping and humanitarian missions rather than with full theater wars (Glade, 2000). With this role change, United States’ vital interests are often not directly at stake. The policymakers are then given more flexibility when responding to situations if technology allows for the completion of missions without risk to human lives. Because of this distinct advantage of utilizing UAVs, one of Congress’ goals for the development of UAVs states that one third of the aircraft in the deep strike force should be unmanned by 2010 (Department of Defense, 2007).

Figure 1. UAV Evolution (Department of Defense, 2001)
Present Roles of UASs

The roles of UASs have expanded greatly within the military in the last few years, and every branch of the U.S. military now employs their own form of a UAS in their intelligence, surveillance, and reconnaissance operations (Cooke, 2006). UASs have played a major role in both Operation Iraqi Freedom and Operation Enduring Freedom, and have done so without putting American pilots’ lives in danger (Scarborough, 2003; Guidry & Wills, 2004).

Although the military is presently the major arena for the operation of UAVs, there is a large amount of interest in expanding current roles of UAVs into domestic and commercial operations. The potential uses of UAVs are numerous in the areas of law enforcement, weather prediction and tracking, agriculture, national security, and many others that have not as of yet been explored. The future of UASs in the national airspace is questionable however, due to the differences in how manned and unmanned aircraft are controlled, as well as current regulations which are not designed for autonomous aircraft.

Future Roles of UASs

The largest hurdle to introducing UAVs into the NAS is the inability of UAVs to “detect, see, and avoid” other traffic (FAA, 2009b). It is of critical importance to the FAA that UAVs don’t come to close to passenger aircraft or endanger people in any way. The process of collision avoidance has many layers to protect aircraft. Figure 2 shows the various layers involved with collision avoidance, and demonstrates how “see and avoid” tactics are a last effort due to non-cooperative air traffic.
Duke Vanderpool and Duke (2007) contend that the FAA is approaching the problem of 'detect, see and avoid' in the wrong manner. The authors argue that under instrument flight conditions (those in which visibility is low and the pilot has to completely rely on the instruments in the aircraft), an unmanned aircraft is no different than a manned aircraft. Because manned aircraft still operate safely under these conditions, UAVs should be afforded the same access to the NAS.

Another major concern for the FAA is the loss of communication between a UAS and the remote operator. Currently, there is no dedicated civil government protected frequency with which to control UASs, and most UASs use military frequencies (DeGarmo & Maroney 2008).
Most UASs are designed to fly a holding pattern when the signal from the operator is lost, but this strategy can potentially cause problems in high traffic areas.

What the FAA demands from UASs, is an equivalent level of safety with manned aircraft (Wilson, 2007). This means that accident rates for UAS flight must match up to that of manned flight. In order to achieve this, technology and human operators must work together to avoid conflicts with other aircraft. The FAA has issued several Certificates of Authorization for flying UAVs in civilian airspace, but only under strict stipulations. The FAA has developed the Unmanned Aircraft Program Office, which reviews applications for flight certificates, and can issue special airworthiness certificates based on those applications (AIR-160, 2008). There are currently a number of organizations working on developing standards to define minimum requirements for UASs, in an effort to address the technological, regulatory, and performance issues with operating UASs (DeGarmo & Maroney, 2008).

*Human Factors Issues with UAS Operation*

The crucial issue in implementing state of the art technologies, such as UASs, is not one of hardware creation, but of the assimilation of sensory inputs, the processing information pertinent to user goals, and translation of the user’s decisions into subsequent actions (Oron-Gilad, Chen, & Hancock, 2006). This means that the main obstacle in successfully employing UASs on a wide scale is inherently a user centered one. In order to reach the full potential of these state of the art technologies, the initial system design must take into consideration the capabilities and limitations of the human operator. This includes the information provided to the human operator, which must support human perception, understanding, reasoning, and decision making in mission environments (Department of Defense, 2007).
England's early efforts at developing UASs were often referred to as 'humans in the loop' which demonstrates recognition of the human role in the system (Newcome, 2004). That recognition, however, has not translated into equivalent levels of effort in developing human factors standards along with the advancement of the technology. The Scientific Advisory Board for the U.S. Air Force has suggested that not enough emphasis has been placed on human systems issues, and recommended that there be an increase in development of human systems concepts within UASs (Worch et al., 1996).

Data collected from the U.S. Army, Navy, and Air Force, regarding the operations of their respective UASs, reveals that accidents among UASs are nearly double those among manned aircraft (Williams, 2004). Many of the accidents analyzed can be directly attributed to human factors issues. A second study looking at UAS accidents categorized the human factors issues prevalent in current UAS technology (Tvaryanas, Thompson, & Constable, 2006). Figure 3 shows some of the conclusions drawn from the study.

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**Figure 3** Categories of mishaps as a percentage of total human factors mishaps by service (Tvaryanas, Thompson, & Constable, 2006)
Identifying human factors problems related to UASs can be difficult due to the fact that problems seen with one type of aircraft would never be seen in another. For example, design problems with the user interface cannot be generalized across different designs due to the fact that the user interfaces vary so much across different types of aircraft (Williams, 2004). The Department of Defense has stated that one of the main objectives in the development of UASs is a common interface which would allow for greater interoperability (Department of Defense, 2007). The current state of UASs is far from realizing this objective. While some UASs have been developed with an interface which is similar to flying a manned aircraft, utilizing throttle and stick controls, others have very different interfaces than those in traditional aviation, and are not as much “flown” as they are “commanded” (Nelson & Bolia, 2006). These types of interfaces utilize a much higher level of automation, which represents a paradigm shift in the way controllers need to think and act when controlling a UAS. Ever increasing levels of automation means that the human user takes on a role of supervisor, and becomes extremely dependant on an adequate interface in order to effectively control the UAS.

**Humans and Automation**

Manufacturers often attempt to automate the human “out of the loop” which means they rely on increasing automation in response to any issues that may arise (Cooke, 2006). This tactic does not however solve human factors issues with the control of UASs, but creates new and distinct challenges to the operators. Even within highly autonomous systems such as UASs, humans are expected to provide high-level objectives, set rules of engagement, supply operational constraints, as well as support launch and recovery operations (Department of Defense, 2007). The use of automation can often cause adverse effects in the performance of the operators using the system, if there is not enough attention paid to human factors issues.
The cause of these effects was termed “clumsy automation” by Wiener and Curry when they were first observed in 1980 (Wiener & Curry, 1980). Since then, it has been recognized that the implementation of automation can change the way human operators perceive situations in ways unintended by the system designers (Billings, 1997; Parasuraman & Riley, 1997). The unintended consequences of the effects automation has on the human operators can then lead to human vigilance decrements, detection capabilities, limited system flexibility, and automation biases (Parasuraman, Sheridan, & Wickens, 2000). These issues with automation provide a number of challenges to implementing highly autonomous systems such as UASs. Billings (1997) provides an answer to these concerns through a number of guidelines to human centered automation:

- The pilot bears responsibility for safety of flight
- Pilots must remain in command of their flights
- The pilot must be actively involved
- The pilot must be adequately informed
- The operator must be able to monitor the automation assisting them
- The automated systems must therefore be predictable
- The automated systems must also monitor the human operator
- Every intelligent system element must know the intent of other intelligent system elements

These guidelines establish automation as a member of a team, which must remain coordinated with the other team members in order to achieve a common goal. This concept has been corroborated by Putzer and Onken (2001), who state that in order for the human operator to make effective decisions, the machine and human must interact dynamically as a single system.
Under these circumstances however, the human operator must still oversee automation to ensure accuracy of the decisions being implemented, particularly when unexpected events occur. The question of which functions to allocate to which part of the system, either human operator or automation, then becomes a difficulty.

Function allocation has been defined as the assignment of required functions to resources, instruments or agents (Sheridan, 1998). The distribution of functions between humans and automation has been a focus of human factors professionals for years. While automation is efficient at performing specified tasks, higher level functions involved with supervising an automated system such as sensing unusual situations in the environment, detecting unusual stimuli, and goal oriented decision making seem to be better suited for human performance (Sanders & McCormick, 1993). More recent function allocation strategies have focused not so much on dividing functions between humans and machines, but designing the system in such a fashion that it produces an effective coordination between the two (Hughes, 2008). Schulte (2002) recommends a similar approach, which leads to a cooperative system design between humans and automation in order to take advantage of the strengths of each. Figure 4 shows examples of resources of different parts of a human-automation system which can be enhanced through man-machine cooperation.
Previous studies on UASs have suggested that increasing the number of functions allocated to automation can result in a decrease in operator workload (Dixon, Wickens, & Chang, 2003). When highly autonomous systems are being used however, human operators can often rely on the automation inappropriately, trusting the machine to perform functions which may be better suited to their own strengths. This overreliance on automation is referred to as *misuse*, whereas not utilizing the advantages of automation is referred to as *disuse* (Parasuraman & Riley, 1997). When automation is either *misused* or *disused*, the system cannot operate as efficiently as possible because the strengths of each component are not being fully utilized. The trend of system design seems to inevitably move towards increasing the level of automation to the greatest extent possible. This design strategy does not allow an adequate level of human involvement, and can lead to failure of the entire system. If the human operator is not able to perform the role of supervisor and act as a fail-safe, it can threaten the safety of not only the UAS itself, but anything else in the vicinity of the aircraft.
The level of automation implemented in the UAS then becomes an important factor in determining how safely and efficiently the system will operate in general. Management by consent and management by exception are the two most common design methods for implementing automation in a user interface. Management by consent is a level of automation in which the automation provides suggestions for action, but does not carry it out until the operator gives approval, while management by exception is a level in which the automation will carry out the recommended course of action unless the operator commands otherwise (McCarley, 2004). Research has found that there are differences in the benefits gained from these two levels of automation in a UAS supervisory monitoring task (Ruff, Narayanan, & Draper, 2002). The different benefits from the levels of automation come with different detriments to performance as well. Increased automation may decrease workload, but may also increase the reliance of the human operator on automation to the point that the automation is being misused. Decreased automation may have the opposite effect on workload, increasing it to dangerous levels, as well as reducing the ability of the user to rely on automation when it may be necessary. The goal becomes to design a system with an appropriate level of automation, which provides the operator with enough information to maintain situation awareness, but not so much as to increase workload. Chun, Spura, Alvidrez, and Stiles (2006) recommended a highly autonomous system with an interface which suggests appropriate responses to situations and factors in operator workload, especially during emergencies when workload becomes heightened.

Workload

Mental workload can be described as the relationship between the mental resources demanded by a task, and those resources available to be supplied by the human operator (Parasuraman, Sheridan, & Wickens, 2008). The implementation of automation can alleviate
excess workload for a wide variety of tasks, and has made possible many complex tasks which would be inconceivable otherwise. The operation of UASs in dangerous airspace is an obvious example of this, but how this high level of automation affects the workload of the operator is an issue which still requires further study.

It is clear that appropriate use of automation within a UAS could potentially lead to the freeing up of human resources to perform more complex tasks for which they are better suited. Dixon, Wickens, and Chang (2003) found that allocation of flight control to automation led to higher performance on concurrent target identification and system failure identification tasks, which the authors attribute to the reduced level of workload. High levels of workload can lead to performance detriments, but it is important to note that workload levels which are too low can have the same effect (Crescenzi, Miranda, Periani, & Bombardi, 2007). Often an operator experiencing low workload levels will lose track of tasks the system is performing, losing situation awareness, and inevitably causing performance problems. When the operator needs to become involved in the system again, such as during an unexpected event, workload increases as they attempt to regain the lost situation awareness.

Not only can automation lead to a high level of workload, but situations which create high workload in the operator can lead to an overreliance on the automation. When workload is too high, and there are not enough cognitive resources available to support a calculated rational choice, operators can simply rely on automation to make a decision for them (Lee & See, 2004). This is often a misuse of the automation and can result in tactical errors. When these types of errors occur during UAS flight, safety becomes compromised and becomes an area of major concern.
Measurement of Workload

Many methods exist to determine level of workload in a human operator, and can be categorized into four groups: operator performance, subjective ratings, analytic methods, and physiological measures. Improper procedures for measuring workload can not only fail to correctly detect level of workload, but can interfere with the operator and have an effect on the workload themselves. Workload measures need to be selected based on their sensitivity, diagnostic capability, and intrusiveness, as these are the most important properties to consider when implementing a measure (Eggemeier, Wilson, Dramer, & Damos, 1991). The sensitivity of a measure refers to the ability to distinguish between different levels of workload. A measure that is not sensitive enough for a given task can produce results which show no change in workload where there actually is a change. Diagnostic capability refers to the ability to distinguish the source of the workload. This is particularly important in complex tasks which involve effort from multiple modalities. Finally, intrusiveness is the level to which the measure interferes with the operator’s ability to perform the primary task. If the measure is distracting or impedes the operator from performing the primary task, it is considered to be highly intrusive.

For the current study, subjective measures have been chosen due to their sensitivity, high face validity, ease of use, and comparability. Previous studies have also utilized subjective measures, and demonstrated their usefulness (Liu, Wasson, & Vincenzi, 2008; Reynolds, 2009). As a subjective rating, the NASA-TLX will be used due to its sensitivity to individual components of mental workload (Hart & Staveland, 1988).

Additionally, performance measures will be utilized in order to directly demonstrate differences in workload. Secondary tasks will add more workload in order to demonstrate the
upper limits of workload not achieved through the primary task alone. It is imperative that the secondary tasks do not intrude on performance of the primary task if they are to be reliable measures of workload. For this reason, participants were instructed that the primary task of target detection will hold priority over other tasks, and should be completed before attention is paid to the secondary tasks.

Task Uncertainty

The fact that human operators are physically separated from the aircraft in a UAS, can cause a problem referred to as out of the loop unfamiliarity in which the operator lacks adequate levels of situation awareness needed to operate a UAS efficiently (Wickens, 1992). Specific problems include poor spatial resolution, limited field of view, low update rates, and delayed image updating (McCarley & Wickens, 2005). The unfamiliarity experienced by operators is a result of not only lack of visual cues, but those from other sensory inputs as well. McCarley and Wickens (2004) studied some of the effects of removing the pilot from the aircraft, and termed this lack of sensory inputs “sensory isolation”. The result of sensory isolation is human operators who show high levels of boredom, decreased recognition performance, and degraded target detection (Tvaryanas, Thompson, & Constable, 2006).

The ability to identify and locate targets in real time is a current shortfall of UAS technology (Department of Defense, 2007). While manned aircraft have the advantage of a relatively wide field of view, UASs are generally limited to a few visual displays, from which the operator must be able to glean a large amount of information. When the capabilities of UASs expanded to carry lethal payloads, the importance of accurate decision making regarding target identification became infinitely more important. The identification of targets is particularly difficult due to the
low fidelity and restricted visual angle available to UAS operators, and this is made even more complicated when the target lies amidst an array of distracting information, which is often the case with military operations. Uncertainty describes the condition an observer experiences when viewing an image which contains confusing distracter items (Vierck & Miller, 2007). When there is a high level of uncertainty in the decision making process, humans will actively search out ways to reduce that uncertainty by gathering more information, and when all else fails, simply suppress the uncertainty and take action (Lipshitz, 1997). These strategies have serious implications in target identification.

To alleviate the uncertainty associated with target identification, and due to the potential for high fratricide rates, many target identification systems have been developed. These systems are designed as an automated decision aid for the identification of friendly troops, but it is not certain whether performance on target identification has actually improved because of problems with human-automation interaction (Galster, Bolia, Roe, & Parasuraman, 2001). Humans show difficulty relying on this type of automation appropriately, particularly when it is imperfect (Wang, Jameson, & Hollands, 2009). Studies have demonstrated that when there is high uncertainty identifying a target in a visual display, by default, operators tend to rely on automation’s ability to make the correct identification (Beck, McKinney, Dzindolet, & Pierce, 2009; Conejo & Wickens, 1997; Dzindolet, Pierce, Beck, Dawe, & Anderson, 2001). The ability of technology to correctly identify a target is not as accurate as a human. This overreliance on automated target identification systems is only exacerbated when a decision needs to be made quickly, as is often the case in combat operations.
Time Pressure

In a time sensitive environment, decision making can become much more taxing on a human operator. Time pressure can have the effect of making a somewhat mundane task more challenging and therefore pleasurable. This suggestion is contrasted by more extreme states occurring when time pressure is so great that people consider a task impossible to complete in an allotted time frame (Maule, 1997). In either case, time pressure adds workload to a task, and in the latter case, that workload exceeds the capacity of the person performing the task. Time pressure may lead to the reallocation of resources from the decision process to stress coping mechanisms, change the goals in a decision situation, as well as modify the structuring and processing of information (Svenson, 1997). This reorganization of cognitive functions can result in an increase in workload associated with the time pressure.

Research has demonstrated the increase in workload due to time pressure, and found that performance decreased as a result (Hughes & Babski-Reeves, 2005). This is particularly evident in tasks which already present high levels of stress to the operator, such as target identification. Another study found that during a target identification task, time pressure resulted in degraded ability to distinguish friend from foe (Burke, Oron-Gilad, Conway, & Hancock, 2007). Situations which cause this type of problem pose a serious threat to military operations through increased fratricide rates.

Researchers have attempted to mediate the excess workload placed on humans when time pressure is introduced by utilizing decision aids. The most beneficial type of decision aid and the best method of implementation is still a topic of disagreement. One study found that displays showing only status information were superior to decision aids in achieving optimal performance
on a decision making task during flight (Sarter, Schroeder, & McGuirl, 2001). The results of this study also point out however, that while performance was enhanced, time to complete the task was increased. When under time pressure, it may be optimal to provide actual command suggestions to the human to alleviate workload. One study found that in a target acquisition task, priming has different effects on performance depending on visual relatedness of the prime to the target, and accuracy of the decision aid (Hailston & Davis, 2006). One drawback of implementing any type of decision aid, particularly in a task such as target detection, is the reliability of the automation. Time pressure can increase workload to the point that humans demonstrate an overreliance on automation (Glade, 2000). This implies that when time pressure increases workload, humans will trust automation to make the correct decision, even when it is known that the automation is not perfectly reliable. This seems to be a coping mechanism to deal with the added stress of time pressure.

Summary

The highly autonomous nature of UASs has advanced the debate about the interaction between humans and automation. The environment in which they operate, and the ability of a human operator to understand and control a UAS within that environment, introduce a significant human factors problem. This is a problem which must be addressed if we are to realize the full potential of this technology. One of the largest road blocks to the full implementation of UASs is a proper user interface which can alleviate some of the problems currently being experienced. In order to determine the efficacy of an interface, we must determine and understand the consequences for the human operator when using that interface.
The history of UASs demonstrates the industry’s focus on developing the technology around task capabilities, with little thought for how the new technology affects the human operator. The reliance on automation to solve any and all issues which arise has caused a drastic change in the role of a human in the system, and little research to support the new role. The main area of importance with regards to UAS research revolves around the idea that the human retains sole responsibility for the system. Future design should implement a human centric approach, and construct the entire system outward from there. This requires a large amount of research into the most beneficial interface with regards to human capabilities and limitations.

One area of limitation humans experience during the control of a UAS is workload, which can range from being excessive enough to cause performance detriments, to being too low to maintain vigilance. These workload effects are difficult to anticipate, particularly with new technology such as an interface which allows the control of multiple UASs. What is not known is how different tasks associated with UAS operation affect workload, and may potentially deteriorate performance.

One of the most important tasks of a UAS is reconnaissance and target identification. This task is well suited for UASs due to the fact that the aircraft can fly above areas believed to contain possible targets without endangering human lives in doing so. The quality of images gathered by a UAS can be limited, thus creating excessive workload for the operator who must correctly identify any targets. The workload is further heightened by the time pressure associated with typical UAS missions. Automation can relieve some of that workload by identifying the targets and making suggestions to the operator, but automation can be inaccurate in doing so. The human operator must retain supervisory control over the entire system, and therefore must be able to verify any target identification before allowing the automation to
execute any tasks. There is a need for further research into target identification tasks while operating a UAS, in order to understand the roles that should be assigned to either the human operator or the automation so that the full potential of human-machine interaction can be achieved.

This study addresses the effect of time pressure and task uncertainty on operator performance and workload while operating a UAS. The following hypotheses were formulated for this study:

Statement of Hypotheses

Hypothesis 1: When participants are exposed to high uncertainty targets, they will report higher workload than when they are exposed to low uncertainty targets.

Hypothesis 2: When participants are exposed to high uncertainty targets, they will score lower on primary task performance measures than when they are exposed to low uncertainty targets.

Hypothesis 3: When participants are exposed to high uncertainty targets, they will score lower on secondary task performance measures than when they are exposed to low uncertainty targets.

Hypothesis 4: When participants experience a three second time limit in target processing, they will report higher workload than when they experience a six second time limit.

Hypothesis 5: When participants experience a three second time limit on target processing, they will score lower on image accuracy than when they experience a six second time limit.
Hypothesis 6: When participants experience a three second time limit on target processing they will score higher on secondary task performance measures than when they experience a six second time limit.

Hypothesis 7: An interaction will exist between time limit on target processing and uncertainty of targets with regard to workload. Specifically, when participants experience a three second time limit, task uncertainty will create less of a workload effect than when they experience a six second time limit.

Hypothesis 8: An interaction will exist between time limit on target processing and uncertainty of targets with regard to secondary task performance. Specifically, when participants experience a three second time limit, task uncertainty will create less of an effect on secondary task performance than when they experience a six second time limit.

Methods

Participants

Thirty participants from Embry-Riddle Aeronautical University were recruited to participate in the study. Participants were offered extra credit in an undergraduate course in exchange for their participation and were asked to sign a consent form acknowledging their willingness to participate in this study (See Appendix A).

Apparatus

The apparatus consisted of a standard computer running a UAS software test bed simulation device called MIHIRO (Multi-modal Immersive Intelligent Interface for Remote Operations).
The MIIIRO test bed has been previously utilized as an UAS simulator (Nelson, Lefebvre, & Andre, 2004; Tso et al., 2003). The software was designed by IA Tech with support from the Air Force Research Laboratory, and is designed to conduct research for and simulate long range, high endurance UASs. The setup included two monitors, the primary of which portrayed the Tactical Situation Display (TSD). The TSD included a topographical image of the operating environment, highlighted routes including waypoints, critical targets, other intruding aircraft, and the Mission Mode Indicators (MMI). The secondary monitor displayed the Image Management Display (IMD) which includes an image cue and image display used for target acquisition.

Figure 5 shows the MIIIRO interface.

![MIIIRO Testbed Display. Left: Tactical Situation Display (TSD); Right: Image Management Display (IMD)](image)

**Figure 5.** MIIIRO Testbed Display. Left: Tactical Situation Display (TSD); Right: Image Management Display (IMD)

**Design**

A 2x2 within subjects, fully factorial design was used for the study. The independent variables were target uncertainty and time pressure. Target uncertainty consisted of high uncertainty images, those with an equal number of distracters similar to the target, and low uncertainty images which will contain either all targets or all distracters. The uncertainty that
this study attempted to elicit is based on probability. With a mix of half targets and half
distracters, the probability of making an incorrect distinction is 50%. With either strictly
distracters or strictly targets, the probability of making an incorrect distinction is lowered,
thereby reducing uncertainty. A management by exception strategy was utilized to create time
pressure for the primary task. The time pressure consisted of either three or six second time
limits during the target acquisition task. These times were determined through a small pilot
study involving two Embry-Riddle Aeronautical University students, which yielded a mean
image processing time of 1953ms. It was determined that a three second time limit would
provide adequate time pressure, while a six second time limit was long enough to provide little to
no time pressure. Dependant measures collected were workload, image processing time, and
accuracy for the primary task. Workload was subjectively reported by participants, while
accuracy and image processing time were objectively measured by the MIIIRO software.
Secondary task measures were also taken by the MIIIRO software, and will be described later.
Refer to Table 1 for a graphical depiction of the experimental design.

Table 1
**Primary Task**

The primary task during this study was target acquisition. The UAS utilized a high level of autonomy and did not require the participant to directly control flight. Preset waypoints made up the flight path which the UAS followed. Along the flight path, 10 image capture locations were preset and images were presented to the participants associating each image capture location with a target acquisition. The participants were required to view the images collected by the aircraft, and verify that the Automatic Target Recognizer (ATR) had correctly selected the targets. Each image contained at least one ground vehicle, but a target was not always present. Distracters were present in some of the images as well, and were discernable from the targets by a combination of color, shade, and hue. The ATR placed a red box around the vehicles it had recognized as targets, although the ATR was not always correct, and sometimes placed the red box around distracters while not placing one around the targets. The reliability of the ATR was set to 80\% in order to make sure the participant was verifying that targets had been correctly selected. In cases where the ATR had incorrectly designated targets and distracters, the participant was required to manually select and deselect the images by clicking on the images with the mouse. The automation processed the images as is, without participant input, if no action was taken within the time limit.

Primary task performance measures were automatically collected by the MIIIRO software. These measures included image processing time and target selection accuracy.

**Secondary Task**

There were three secondary tasks that the participants were required to perform during this experiment. The first task consisted of processing Intruder Aircraft (IA) which entered the
operational airspace. This task was used to imitate unexpected aircraft which may enter airspace during typical UAS operation, which is a highly critical situation, and requires a quick and attentive response. The IA was depicted by a red aircraft shaped icon appearing on the display at random times during the experiment. This event occurred twice for each trial, and resulted in the participant being required to click on the aircraft and enter a predetermined code.

The second task involved the MMI, which was represented by three round lights organized in a line, similar to a horizontal stoplight, displayed on the TSD. The MMI indicated the status of the UAS by lighting up the green, yellow, or red light which indicate a state of good health, action needed, and urgent action needed, respectively. In order to correct the situation in the event that the yellow or red lights are illuminated, the participant needed to click on the light panel and correctly type in a text string which was presented to the participant via a pop up window after initiating the action. Once the text string was entered correctly, the MMI returned to a state of good health and illuminated the green light.

The third task in this experiment required the participant to respond to flight path change recommendations made by the automation. “Pop-up threats” were designed into the flight path, but were not visible to the participant until the aircraft had encountered them. When this occurred, the automation made a recommendation on a route change to avoid the threat, and the participant was required to acknowledge and accept the recommended change before it was put into effect. The route changes recommended were not always necessary, so the participant had the ability to reject the route change in favor of the original flight plan if they decided to do so. Data for all three of the additional tasks was automatically collected by the MIIIRO software and included the number of events and response times for all MMI, IA, and pop-up threat occurrences.
A NASA-TLX rating scale was utilized to measure the participants' workload (Hart & Staveland, 1988). The NASA-TLX measure provided an overall workload score based on a weighted average of six subscales which include mental demands, physical demands, temporal demands, performance effort, and frustration.

Procedure

Once each participant arrived at the lab, they were asked to fill out the consent form (Appendix A) and biographical questionnaire (Appendix B). The participant was then introduced to the NASA-TLX questionnaire (Appendix C), and it was explained to them how to fill out the form. There was then an introduction to the MIIIRO simulator and the participants were informed of the purpose of the experiment. Familiarization with the simulator included an instructional session with a hands-on training exercise which covered all possible events that occurred during the actual experiment and lasted five minutes. If the participant had any questions, they were answered at this time.

After the participants had been briefed and completed the training session, they began the experiment and no additional help was available to them. Each participant completed all of the scenarios, the order of which was randomized with regards to time pressure and image uncertainty to avoid any learning effects. Each trial lasted approximately seven minutes and immediately following the trial the participants filled out the workload questionnaire. Once this was completed, the participants were debriefed and any further questions were answered. Once the entire study was completed, the highest performing participant was contacted to receive $100.
Results

The current study was intended to investigate the effect of time pressure and task uncertainty on autonomous unmanned aerial vehicle operator workload and task performance. Repeated measures ANOVA's were used to analyze each of the effect each independent variable had on the dependent variables: image processing time, image accuracy, MMI processing time, IA processing time, pop-up threat processing time, and workload measured by NASA-TLX. An alpha value of 0.05 was used to determine significance.

Image Processing Time

There were two primary task performance measures collected during this study. The first of these was image processing time, and the second was image accuracy. Hypothesis 2 stated that high task uncertainty would result in lower primary task performance measures, which in this case means higher image processing times and lower image accuracy. Hypothesis 5 stated that a lower time limit would increase the time pressure on the participants and result in lower image accuracy. The means and standard deviations for image processing time are presented in Table 2. To test these hypotheses, an ANOVA was conducted to determine if there was any significant difference between the scenarios with regard to image processing time and image accuracy. The results of the ANOVA for image processing time are presented first, and are shown in Table 3.
### Table 2

Means and Standard Deviations for Image Processing Times (ms)

<table>
<thead>
<tr>
<th>Source</th>
<th>Mean</th>
<th>Standard Dev.</th>
<th>Lower Bound</th>
<th>Upper Bound</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Time Pressure</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High</td>
<td>2253.92</td>
<td>49.67</td>
<td>2152.33</td>
<td>2355.51</td>
</tr>
<tr>
<td>Low</td>
<td>2745.32</td>
<td>98.80</td>
<td>2543.25</td>
<td>2947.39</td>
</tr>
<tr>
<td><strong>Uncertainty</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High</td>
<td>2417.57</td>
<td>77.67</td>
<td>2258.72</td>
<td>2576.42</td>
</tr>
<tr>
<td>Low</td>
<td>2581.67</td>
<td>72.29</td>
<td>2433.82</td>
<td>2729.51</td>
</tr>
</tbody>
</table>

### Table 3

ANOVA Source Table for Image Processing Time (ms)

<table>
<thead>
<tr>
<th>Source</th>
<th>SS</th>
<th>df</th>
<th>MS</th>
<th>F</th>
<th>p</th>
<th>Power</th>
</tr>
</thead>
<tbody>
<tr>
<td>Uncertainty</td>
<td>807864.30</td>
<td>1</td>
<td>807864.30</td>
<td>5.57</td>
<td>.025*</td>
<td>.626</td>
</tr>
<tr>
<td>Time Pressure</td>
<td>7244218.80</td>
<td>1</td>
<td>7244218.80</td>
<td>35.64</td>
<td>.000*</td>
<td>1</td>
</tr>
<tr>
<td>Time Pressure* Uncertainty</td>
<td>1960963.33</td>
<td>1</td>
<td>1960963.33</td>
<td>9.28</td>
<td>.005*</td>
<td>.838</td>
</tr>
<tr>
<td>Error (Uncertainty)</td>
<td>4205627.20</td>
<td>29</td>
<td>145021.63</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Error (Time Pressure)</td>
<td>5894608.70</td>
<td>29</td>
<td>203262.37</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*p < .05.

The effect of uncertainty on image processing time was examined first. These means differed significantly at $F(1.29)=5.571$, $p=.025$. An observed power of 0.626 gives backing to these results. As shown in Figure 6, low task uncertainty produced longer image processing times than high task uncertainty, contradicting the prediction made in hypothesis 2.
Figure 6. Uncertainty effect on image processing time

The effect of time pressure on image processing time was also analyzed. These means differed significantly at F(1,29)=35.64, p=.000. An observed power of 1.0 adds backing to this finding. The results are shown in Figure 7.

Figure 7. Time pressure effect on image processing time

In addition to the main effects reported previously, there was a significant interaction between time pressure and uncertainty for image processing time. The means and standard deviations are presented in Table 4.
Table 4

Means and Standard Deviations for the Interaction of Time Pressure and Uncertainty on Image Processing Time (ms)

<table>
<thead>
<tr>
<th>Time Pressure</th>
<th>Uncertainty</th>
<th>Mean</th>
<th>Standard Dev.</th>
<th>Lower Bound</th>
<th>Upper Bound</th>
</tr>
</thead>
<tbody>
<tr>
<td>High</td>
<td>High</td>
<td>2299.70</td>
<td>47.40</td>
<td>2202.77</td>
<td>2396.63</td>
</tr>
<tr>
<td></td>
<td>Low</td>
<td>2208.13</td>
<td>64.69</td>
<td>2075.82</td>
<td>2340.45</td>
</tr>
<tr>
<td>Low</td>
<td>High</td>
<td>2535.43</td>
<td>132.81</td>
<td>2263.80</td>
<td>2807.07</td>
</tr>
<tr>
<td></td>
<td>Low</td>
<td>2955.20</td>
<td>110.74</td>
<td>2728.72</td>
<td>3181.68</td>
</tr>
</tbody>
</table>

This interaction was found to be significant at F(1,29)=9.28, p=.005. The significance of this interaction indicates that at high time pressure, uncertainty has less of an effect than at low time pressure. The results of this interaction are shown in Figure 8.

![Image Processing Time (ms)](image)

Figure 8. Time pressure by uncertainty image processing time

*Image Accuracy*

Image accuracy is the second of two primary task performance measures collected during the study. Again, hypothesis 2 stated that high task uncertainty would result in lower image
accuracy and hypothesis 5 stated that a lower time limit would increase the time pressure on the participants resulting in lower image accuracy. The means and standard deviations for image accuracy are presented in Table 5, and the results of the ANOVA are presented in Table 6.

Table 5

Means and Standard Deviations for Image Accuracy (%)  

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Standard Dev.</th>
<th>Lower Bound</th>
<th>Upper Bound</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time Pressure</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High</td>
<td>84.67</td>
<td>2.31</td>
<td>79.94</td>
<td>89.39</td>
</tr>
<tr>
<td>Low</td>
<td>84.35</td>
<td>2.05</td>
<td>80.17</td>
<td>88.53</td>
</tr>
<tr>
<td>Uncertainty</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High</td>
<td>92.67</td>
<td>1.24</td>
<td>90.13</td>
<td>95.20</td>
</tr>
<tr>
<td>Low</td>
<td>76.35</td>
<td>3.18</td>
<td>69.86</td>
<td>82.84</td>
</tr>
</tbody>
</table>

Table 6

ANOVA Source Table for Image Accuracy (%)  

<table>
<thead>
<tr>
<th>Source</th>
<th>SS</th>
<th>df</th>
<th>MS</th>
<th>f</th>
<th>p</th>
<th>Power</th>
</tr>
</thead>
<tbody>
<tr>
<td>Uncertainty</td>
<td>7987.01</td>
<td>1</td>
<td>7987.01</td>
<td>39.98</td>
<td>.000*</td>
<td></td>
</tr>
<tr>
<td>Time Pressure</td>
<td>3.01</td>
<td>1</td>
<td>3.01</td>
<td>.041</td>
<td>.842</td>
<td>.054</td>
</tr>
<tr>
<td>Time Pressure* Uncertainty</td>
<td>1197.01</td>
<td>1</td>
<td>1197.01</td>
<td>18.73</td>
<td>.000*</td>
<td>.987</td>
</tr>
<tr>
<td>Error (Uncertainty)</td>
<td>5793.24</td>
<td>29</td>
<td>199.77</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Error (Time Pressure)</td>
<td>2147.24</td>
<td>29</td>
<td>74.04</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* p < .05.

The effect of time pressure on image accuracy was analyzed, and the means did not demonstrate a significant difference at \( F(1,29) = 0.041, p = .842 \), thus hypothesis 5 is not supported for image accuracy. The means for uncertainty differed significantly at \( F(1,29) = 39.98, p = .000 \).
Hypothesis 2 stated that high uncertainty would result in lower image accuracy, which is contradicted by these results, shown in Figure 9.

![Image Accuracy](image.png)

Figure 9. Uncertainty effect on image accuracy

A significant interaction was also found for image accuracy $F(1,29)=18.73, p=.000$. The means and standard deviations are presented in Table 7, and the interaction is shown in Figure 10.

Table 7

<table>
<thead>
<tr>
<th>Time Pressure</th>
<th>Uncertainty</th>
<th>Mean</th>
<th>Standard Dev.</th>
<th>Lower Bound</th>
<th>Upper Bound</th>
</tr>
</thead>
<tbody>
<tr>
<td>High</td>
<td>High</td>
<td>89.67</td>
<td>1.89</td>
<td>85.81</td>
<td>93.53</td>
</tr>
<tr>
<td></td>
<td>Low</td>
<td>79.67</td>
<td>3.54</td>
<td>72.43</td>
<td>86.91</td>
</tr>
<tr>
<td>Low</td>
<td>High</td>
<td>73.03</td>
<td>3.20</td>
<td>66.50</td>
<td>79.57</td>
</tr>
<tr>
<td></td>
<td>Low</td>
<td>95.67</td>
<td>1.24</td>
<td>93.13</td>
<td>98.20</td>
</tr>
</tbody>
</table>
In addition to the primary task performance measures, there were also three secondary performance measures collected during this study. These secondary task performance measures include MMI processing time, IA processing time, and the pop-up threat processing time. Hypothesis 3 stated that high task uncertainty would result in lower secondary task performance measures, which in this case means higher processing times for all secondary tasks. Hypothesis 6 stated that a lower time limit would result in higher performance on secondary tasks, meaning lower processing times on all secondary tasks. Hypothesis 8 also stated an interaction to occur between time limit and task uncertainty with regards to secondary task performance. To test these hypotheses, an ANOVA was conducted for each secondary task. MMI processing time was analyzed first. The means and standard deviations are presented in Table 8, followed by the ANOVA results presented in Table 9.
Table 8
Means and Standard Deviations for MMI Processing Time (ms)

<table>
<thead>
<tr>
<th>Source</th>
<th>Mean</th>
<th>Standard Dev.</th>
<th>Lower Bound</th>
<th>Upper Bound</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time Pressure</td>
<td>High</td>
<td>7984.90</td>
<td>366.08</td>
<td>7236.19</td>
</tr>
<tr>
<td></td>
<td>Low</td>
<td>8227.78</td>
<td>365.13</td>
<td>7481.01</td>
</tr>
<tr>
<td>Uncertainty</td>
<td>High</td>
<td>8054.55</td>
<td>359.81</td>
<td>7318.66</td>
</tr>
<tr>
<td></td>
<td>Low</td>
<td>8158.13</td>
<td>365.68</td>
<td>7410.23</td>
</tr>
</tbody>
</table>

Table 9
ANOVA Source Table for MMI Processing Time (ms)

<table>
<thead>
<tr>
<th>Source</th>
<th>SS</th>
<th>df</th>
<th>MS</th>
<th>f</th>
<th>p</th>
<th>Power</th>
</tr>
</thead>
<tbody>
<tr>
<td>Uncertainty</td>
<td>321885.21</td>
<td>1</td>
<td>321885.21</td>
<td>.232</td>
<td>.633</td>
<td>.075</td>
</tr>
<tr>
<td>Time Pressure</td>
<td>1769769.41</td>
<td>1</td>
<td>1769769.41</td>
<td>1.083</td>
<td>.307</td>
<td>.172</td>
</tr>
<tr>
<td>Time Pressure* Uncertainty</td>
<td>1.023xe7</td>
<td>1</td>
<td>1.023xe7</td>
<td>7.156</td>
<td>.012*</td>
<td>.734</td>
</tr>
<tr>
<td>Error (Uncertainty)</td>
<td>4.019xe7</td>
<td>29</td>
<td>1385793.62</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Error (Time Pressure)</td>
<td>4.740xe7</td>
<td>29</td>
<td>1634403.10</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* p < .05.

The means for the effect of uncertainty on MMI processing time did not differ significantly at F(1,29)=.232, p=.633, which does not support hypothesis 3. The means for the effect of time pressure on MMI processing time also did not differ significantly at F(1,29)=1.083, p=.307, which does not support hypothesis 6. An interaction between time pressure and uncertainty however, was found to be significant at F(1,29)=7.156, p=.012, with an observed power of .734. The means and standard deviations for this interaction are presented in Table 10, and the results are shown in Figure 11.
Table 10

Means and Standard Deviations for the Interaction of Time Pressure and Uncertainty on MMI Processing Time (ms)

<table>
<thead>
<tr>
<th>Time Pressure</th>
<th>Uncertainty</th>
<th>Mean</th>
<th>Standard Dev.</th>
<th>Lower Bound</th>
<th>Upper Bound</th>
</tr>
</thead>
<tbody>
<tr>
<td>High</td>
<td>High</td>
<td>8225.13</td>
<td>397.95</td>
<td>7411.23</td>
<td>9039.03</td>
</tr>
<tr>
<td></td>
<td>Low</td>
<td>7744.67</td>
<td>412.17</td>
<td>6901.69</td>
<td>8587.64</td>
</tr>
<tr>
<td>Low</td>
<td>High</td>
<td>7883.97</td>
<td>368.21</td>
<td>7130.90</td>
<td>8637.03</td>
</tr>
<tr>
<td></td>
<td>Low</td>
<td>8571.60</td>
<td>405.83</td>
<td>7741.58</td>
<td>9401.62</td>
</tr>
</tbody>
</table>

Figure 11. Time pressure by uncertainty MMI processing time

**IA Processing Time**

The next secondary task measure presented here is IA processing time. Hypothesis 3 stated that high task uncertainty would result in higher IA processing times, while hypothesis 6 stated that a lower time limit would result in lower IA processing times. Hypothesis 8 also stated an interaction to occur between time limit and task uncertainty with regards to IA processing
times. The means and standard deviations for IA processing time are presented in Table 11, and
the ANOVA table for IA processing time is presented in Table 12.

Table 11
Means and Standard Deviations for IA Processing Time (ms)

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Standard Dev.</th>
<th>Lower Bound</th>
<th>Upper Bound</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Time Pressure</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High</td>
<td>6357.40</td>
<td>314.51</td>
<td>5714.15</td>
<td>7000.65</td>
</tr>
<tr>
<td>Low</td>
<td>5825.08</td>
<td>295.65</td>
<td>5220.41</td>
<td>6429.76</td>
</tr>
<tr>
<td><strong>Uncertainty</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High</td>
<td>5753.38</td>
<td>261.21</td>
<td>5219.16</td>
<td>6287.61</td>
</tr>
<tr>
<td>Low</td>
<td>6429.10</td>
<td>380.50</td>
<td>5650.89</td>
<td>7207.31</td>
</tr>
</tbody>
</table>

Table 12
ANOVA Source Table for IA Processing Time (ms)

<table>
<thead>
<tr>
<th>Source</th>
<th>SS</th>
<th>df</th>
<th>MS</th>
<th>f</th>
<th>p</th>
<th>Power</th>
</tr>
</thead>
<tbody>
<tr>
<td>Uncertainty</td>
<td>1.370e7</td>
<td>1</td>
<td>1.370e7</td>
<td>2.51</td>
<td>.124</td>
<td>.334</td>
</tr>
<tr>
<td>Time Pressure</td>
<td>8500831.01</td>
<td>1</td>
<td>8500831.01</td>
<td>2.20</td>
<td>.148</td>
<td>.300</td>
</tr>
<tr>
<td>Time Pressure*</td>
<td>1.325e7</td>
<td>1</td>
<td>1.325e7</td>
<td>2.915</td>
<td>.098</td>
<td>.379</td>
</tr>
<tr>
<td>Uncertainty</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Error (Uncertainty)</td>
<td>1.583e8</td>
<td>29</td>
<td>5458427.56</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Error (Time Pressure)</td>
<td>3857586.92</td>
<td>29</td>
<td>3857586.92</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* p < .05.

The main effect of uncertainty on IA processing time was not found to be significant at
F(1,29)=2.51, p=.124, which does not support hypothesis 3. The main effect of time pressure on
IA processing time was also not found to be significant at F(1,29)=2.20, p=.148 which does not
support hypothesis 6. Lastly, the interaction of time pressure and uncertainty was also not found
to be significant at $F(1,29)=2.915$, $p=.098$, and thus does not support hypothesis 8. The means and standard deviations for this interaction are presented in Table 13.

Table 13

Means and Standard Deviations for the Interaction of Time Pressure and Uncertainty on IA Processing Time (ms)

<table>
<thead>
<tr>
<th>Time Pressure</th>
<th>Uncertainty</th>
<th>Mean</th>
<th>Standard Dev.</th>
<th>Lower Bound</th>
<th>Upper Bound</th>
</tr>
</thead>
<tbody>
<tr>
<td>High</td>
<td>High</td>
<td>6351.87</td>
<td>389.51</td>
<td>5555.24</td>
<td>7148.50</td>
</tr>
<tr>
<td></td>
<td>Low</td>
<td>6362.93</td>
<td>459.87</td>
<td>5422.40</td>
<td>7303.47</td>
</tr>
<tr>
<td>Low</td>
<td>High</td>
<td>5154.90</td>
<td>289.77</td>
<td>4562.25</td>
<td>5747.55</td>
</tr>
<tr>
<td></td>
<td>Low</td>
<td>6495.27</td>
<td>508.90</td>
<td>5454.44</td>
<td>7536.09</td>
</tr>
</tbody>
</table>

*Pop-up Threat Processing Time*

The last secondary task measure collected in the current study is pop-up threat processing time. This measure is the time taken to respond to a recommended flight path change due to a threat which pops-up during the simulation. In the same fashion as the other secondary tasks, hypothesis 3 stated that high task uncertainty would result in higher pop-up threat processing times, hypothesis 6 stated that a lower time limit would result in lower pop-up threat processing times, and hypothesis 8 also stated an interaction to occur between time limit and task uncertainty with regards to pop-up threat processing times. The means and standard deviations are presented in Table 14, and the ANOVA table for pop-up threat processing time is presented in Table 15.
Table 14

Means and Standard Deviations for Pop-up Threat Processing Time (ms)

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Standard Dev.</th>
<th>Lower Bound</th>
<th>Upper Bound</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Time Pressure</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High</td>
<td>2896.28</td>
<td>150.53</td>
<td>2588.42</td>
<td>3204.15</td>
</tr>
<tr>
<td>Low</td>
<td>2966.98</td>
<td>109.36</td>
<td>2743.33</td>
<td>3190.64</td>
</tr>
<tr>
<td><strong>Uncertainty</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High</td>
<td>2776.58</td>
<td>124.31</td>
<td>2522.35</td>
<td>3030.82</td>
</tr>
<tr>
<td>Low</td>
<td>3086.68</td>
<td>125.77</td>
<td>2829.45</td>
<td>3343.91</td>
</tr>
</tbody>
</table>

Table 15

ANOVA Source Table for Pop-up Threat Processing Time (ms)

<table>
<thead>
<tr>
<th>Source</th>
<th>SS</th>
<th>df</th>
<th>MS</th>
<th>F</th>
<th>p</th>
<th>Power</th>
</tr>
</thead>
<tbody>
<tr>
<td>Uncertainty</td>
<td>2884860.30</td>
<td>1</td>
<td>2884860.30</td>
<td>6.306</td>
<td>.018*</td>
<td>.680</td>
</tr>
<tr>
<td>Time Pressure</td>
<td>149954.70</td>
<td>1</td>
<td>149954.70</td>
<td>.228</td>
<td>.637</td>
<td>.075</td>
</tr>
<tr>
<td>Time Pressure*Uncertainty</td>
<td>4247298.13</td>
<td>1</td>
<td>4247298.13</td>
<td>6.941</td>
<td>.013*</td>
<td>.721</td>
</tr>
<tr>
<td>Error (Uncertainty)</td>
<td>1.327xe7</td>
<td>29</td>
<td>457485.27</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Error (Time Pressure)</td>
<td>1.909xe7</td>
<td>29</td>
<td>658290.08</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* p < .05.

The main effect for time pressure on pop-up threat processing time did not show significance at F(1,29)=.228, p=.637, thus not supporting hypothesis 6. The main effect for uncertainty on pop-up threat processing time did show a significant difference at F(1,29)=6.306, p=.018, and an observed power of .680 lends some support to the results. These results contradict the prediction made by hypothesis 3, that high uncertainty would lead to higher processing times. The results are shown in Figure 12.
Additionally, an interaction between time pressure and uncertainty was found to have significance for pop-up threat processing time at $F(1,29)=6.941, p=.013$. These results contradict the prediction made by hypothesis 8. The means and standard deviations are presented in Table 16, and the interaction is shown in Figure 13.

Table 16

Means and Standard Deviations for the Interaction of Time Pressure and Uncertainty on Pop-up Threat Processing Time (ms)

<table>
<thead>
<tr>
<th>Time Pressure</th>
<th>Uncertainty</th>
<th>Mean</th>
<th>Standard Dev.</th>
<th>Lower Bound</th>
<th>Upper Bound</th>
</tr>
</thead>
<tbody>
<tr>
<td>High</td>
<td>High</td>
<td>2553.10</td>
<td>189.78</td>
<td>2164.95</td>
<td>2941.25</td>
</tr>
<tr>
<td></td>
<td>Low</td>
<td>3239.47</td>
<td>180.27</td>
<td>2870.77</td>
<td>3608.16</td>
</tr>
<tr>
<td>Low</td>
<td>High</td>
<td>3000.07</td>
<td>138.99</td>
<td>2715.80</td>
<td>3284.34</td>
</tr>
<tr>
<td></td>
<td>Low</td>
<td>2933.90</td>
<td>130.57</td>
<td>2666.86</td>
<td>3200.95</td>
</tr>
</tbody>
</table>
Workload

Workload was measured subjectively using the NASA-TLX after each scenario. The subjective ratings were on a scale ranging from 0 to 100, with 100 being the highest level of workload and 0 being the lowest. Hypotheses 1, 4, and 7 refer to workload. Hypothesis 1 stated that high uncertainty would result in higher workload ratings, and hypothesis 4 stated that high time pressure would also result in higher workload ratings. Hypothesis 7 stated that an interaction would exist between time pressure and uncertainty with regards to workload, and that uncertainty will have less of an effect on workload for scenarios presenting high time pressure than for scenarios presenting low time pressure. The means and standard deviations for workload are presented in Table 17, and the ANOVA table for workload is presented in Table 18.
Table 17
Means and Standard Deviations for Workload

<table>
<thead>
<tr>
<th>Source</th>
<th>Mean</th>
<th>Standard Dev.</th>
<th>95(^{th}) Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time Pressure</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High</td>
<td>44.25</td>
<td>3.23</td>
<td>37.64 – 50.86</td>
</tr>
<tr>
<td>Low</td>
<td>38.72</td>
<td>3.30</td>
<td>31.97 – 45.46</td>
</tr>
<tr>
<td>Uncertainty</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High</td>
<td>41.12</td>
<td>2.96</td>
<td>35.08 – 47.17</td>
</tr>
<tr>
<td>Low</td>
<td>41.85</td>
<td>3.44</td>
<td>34.82 – 48.87</td>
</tr>
</tbody>
</table>

Table 18
ANOVA Source Table for Workload

<table>
<thead>
<tr>
<th>Source</th>
<th>SS</th>
<th>df</th>
<th>MS</th>
<th>(f)</th>
<th>(p)</th>
<th>Power</th>
</tr>
</thead>
<tbody>
<tr>
<td>Uncertainty</td>
<td>15.66</td>
<td>1</td>
<td>15.66</td>
<td>.209</td>
<td>.651</td>
<td>.073</td>
</tr>
<tr>
<td>Time Pressure</td>
<td>918.59</td>
<td>1</td>
<td>918.59</td>
<td>7.512</td>
<td>.010*</td>
<td>.755</td>
</tr>
<tr>
<td>Time Pressure*</td>
<td>37.02</td>
<td>1</td>
<td>37.02</td>
<td>.263</td>
<td>.612</td>
<td>.079</td>
</tr>
<tr>
<td>Uncertainty</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Error (Uncertainty)</td>
<td>2168.10</td>
<td>29</td>
<td>74.76</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Error (Time Pressure)</td>
<td>3546.26</td>
<td>29</td>
<td>122.29</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* \(p < .05\).

The main effect for uncertainty did not show a significant difference at \(F(1, 29) = 0.209, p = 0.651\). The effect of time pressure on workload did show significance at \(F(1, 29) = 7.512, p = 0.01\). With an observed power of \(0.755\), these results lend support to hypothesis 4, that high time pressure would produce higher workload. The means and standard deviations for the interaction of time pressure and uncertainty on workload are presented in Table 19. This interaction did not produce significant results at \(F(1, 29) = 0.263, p = 0.612\), which does not support hypothesis 7. The results for the effect of time pressure on workload are presented on Figure 14.
Table 19
Means and Standard Deviations for the Interaction of Time Pressure and Uncertainty on Workload

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Standard Dev.</th>
<th>Lower Bound</th>
<th>Upper Bound</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Time Pressure</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Uncertainty</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High</td>
<td>44.44</td>
<td>3.20</td>
<td>37.90</td>
<td>50.98</td>
</tr>
<tr>
<td>Low</td>
<td>44.06</td>
<td>3.97</td>
<td>35.94</td>
<td>52.17</td>
</tr>
<tr>
<td>Low</td>
<td>37.80</td>
<td>3.36</td>
<td>30.92</td>
<td>44.68</td>
</tr>
<tr>
<td>Low</td>
<td>39.63</td>
<td>3.54</td>
<td>32.39</td>
<td>46.88</td>
</tr>
</tbody>
</table>

Figure 14. Time pressure effect on workload

Discussion

The objective of this study was to examine the effect of time pressure and task uncertainty on operator task performance and workload when conducting an unmanned aerial vehicle operation. This study was intended to advance current knowledge about the workload associated with operating a highly autonomous UAS, particularly with technology which can provide uncertainty during tasks, and during operations which are extremely time sensitive. The
aim is to provide knowledge which can be applied to the design of future UAS’s in order to improve operator performance through appropriate levels of workload. This knowledge potentially includes the amount of uncertainty an operator can deal with while still maintaining a high level of performance, as well as what level of time pressure the operator can handle before performance begins to deteriorate. The results of this study are discussed here, organized into three main areas of interest: primary task performance measures, secondary task performance measures, and workload.

**Primary Task Performance Measures**

There were two primary task performance measures collected during this study: image processing time and image accuracy. Image processing time showed significance for both level of uncertainty and time pressure. There was also found to be a significant interaction of time pressure and uncertainty with regards to image processing time. Low uncertainty images produced higher image processing times than high uncertainty images. This directly contradicts predictions made about uncertainty and image processing time. It was expected that the more uncertainty an image contained, based on probability, the more time it would take the participant to process that image. It is possible that the different images created different scanning patterns within the participants, and the time it took to scan the images created a difference in processing time. Another possible explanation for these results involves the type of uncertainty chosen as a variable. Uncertainty as a probability simply claims that if 100% of the items displayed on the image are either targets or distracters, there will be little uncertainty about which they are. Images that display 50% targets and 50% distracters would constitute higher uncertainty for the participant. This may not be an accurate representation of uncertainty when making quick decisions during this study. When viewing images which contain both targets and distracters, it
may be easier to determine a difference between the two with only a quick glance, due to the immediate comparison available. When viewing images with strictly targets or strictly distracters, there is no immediate comparison available, making it necessary to examine the image more closely. This is discussed further in the Recommendations for Further Research section.

There was also significance found for time pressure on image processing time. Low time pressure produced longer image processing times than high time pressure. The fact that the participants were under more time pressure to process the images possibly led them to hurry when performing this task. This may negatively affect the accuracy of their responses, but the image processing time would decrease in this case.

The interaction of time pressure and uncertainty showed significant results for image processing time as well. High uncertainty images were processed faster than low uncertainty images at low time pressures, but processed slower at high time pressures. In other words, the effect of time pressure showed a greater change for low uncertainty images than for high uncertainty images. This interaction was not hypothesized to be significant, but a possible explanation for this occurrence is related to the previous statement about the nature of the uncertainty of the images used. When not pressured for time, participants may have been able to more carefully examine the images which did not contain a direct comparison within them. When under a more stringent time constraint, participants may have resorted to guessing, resulting in lower processing times. Reynolds (2009) came to a similar conclusion, and theorized that for processing non-obvious images, participants may simply guess.
The other primary performance measure collected during this study was image accuracy. There was a significant interaction found between time pressure and uncertainty for image accuracy. Uncertainty demonstrated a stronger effect at low time pressure than at high time pressure. This, again, may support the argument that images which have both targets and distracters provide a direct comparison, and lead to higher accuracy. There was also significance found for the main effect of uncertainty on image accuracy. Low uncertainty images yielded a lower accuracy score than high uncertainty images, which contradicts hypothesis 2, but may support the previously stated argument that when participants have no immediate comparisons available to them, the uncertainty may actually increase.

Secondary Task Performance Measures

Secondary task measures were used as another measure of workload, attempting to determine how much excess capacity was available while performing the primary task. There were three secondary task performance measures involved in the current study: MMI processing time, IA processing time, and pop-up threat processing time. Overall, the main effects of the secondary task measures did not agree with the subjective workload ratings from the NASA-TLX. The secondary task measures showed no significance for the effect of time pressure while the workload ratings did show significance. Uncertainty did show a significant main effect for two of the three secondary tasks, while not showing a significant effect on the subjective ratings. This may indicate that the secondary task measures were not an adequate measure of excess capacity as intended, or that the NASA-TLX is simply a more sensitive measure.

MMI processing required the participants to respond to either a yellow or red light within the indicator, by clicking on the light and typing in a number string given to them. MMI
processing time showed no significant results for the main effects of either time pressure or uncertainty. This lack of significance does not support hypotheses 3 or 6, which both stated an effect on secondary performance measures due to uncertainty and time pressure respectively. The interaction of the two however, was shown to contain significance. Again, at low time pressure, scenarios with low uncertainty produced higher MMI processing times than scenarios with high uncertainty, and the opposite is true at high time pressure. Due to the participants being instructed that image processing should be given priority over secondary tasks, it is evident that when participants take longer to process the images, as in the case of the low uncertainty images, secondary task performance is affected. This may be an explanation which fits the data for the interaction, given the data for image processing time, as it contains the same pattern of interaction.

IA processing required the participants to respond to a red aircraft icon which would appear on the tactical situation display, by clicking on the icon and typing in a code given to them. IA processing time yielded no significant differences for effect of time pressure, uncertainty, or their interaction. This again, does not support either hypothesis 3 or 6 for performance on secondary task measures. A possible explanation for this lack of significance is the number of IA events experienced during the trials. For MMI events, performance was affected more by primary task because each scenario contained ten instances of MMI events. This led to more chances for the tasks to overlap and have an effect. IA events on the other hand, occurred only twice per trial. With such a few opportunities for the tasks to conflict, the uncertainty and time pressure placed on the primary task had little chance to affect performance on IA processing.
The last secondary task measure collected was pop-up threat processing time. Pop-up threat processing required the participants to either accept or reject a recommended flight path change in order to avoid a threat which had appeared during the simulation. Uncertainty demonstrated a significant effect on pop-up threat processing time, with low uncertainty resulting in greater processing times than high uncertainty. There was also an interaction between uncertainty and time pressure which demonstrated significance. This time however, the pattern of the interaction is the opposite of interactions on other tasks. At low time pressure, high uncertainty scenarios produced higher processing times than low uncertainty scenarios, and vice versa for high time pressure. This may be due to the nature of the task involved with processing a pop-up threat, which is something that may require further study. The effect of the interaction is greater for high time pressure than for low time pressure, which is in contrast with hypothesis 8.

Workload

Workload was assessed using subjective ratings from the NASA-TLX after each trial. The main effect of uncertainty was not shown to be significant on subjective workload ratings, which contradicts hypothesis 1. The interaction of time pressure and uncertainty also failed to show significance, in contrast with hypothesis 7. The lack of significance for uncertainty, as well as the interaction of time pressure and uncertainty, does not support the argument that lack of direct comparison played a role in how the participants dealt with the images at different time pressures. This idea will be discussed further in Recommendations for Further Research section. Time pressure however, did show significance for the main effect on subjective workload. High time pressure produced higher ratings of subjective workload among the participants, which
supports hypothesis 4. Previous studies using a timeout feature for management by exception have not shown any significance for subjective workload, and it was theorized that participants were not utilizing the timeout feature because the time limit was too long (Reynolds, 2009). This was the basis for the current study, to limit the time the participant had to respond to the images in order to create greater time pressure associated with the task, and determine how this would affect workload. These results demonstrated that workload can be increased by implementing a more stringent time pressure during an image identification task.

Study Limitations

This study was based on previous research using the MIIIRO test bed (Liu, Wasson, & Vincenzi, 2008; Reynolds, 2009). The previous studies showed difficulty in manipulating workload through level of automation, and quality of images was reasoned to be a possible explanation for this. The current study set out to investigate whether image uncertainty could contribute to operator workload. In attempting to define uncertainty however, several possibilities arose as methods for manipulating uncertainty. The method chosen was based on probability, that is, if an image contains strictly targets, the participant has no chance of erroneously selecting a distracter, leaving little uncertainty. If the image however, contains half targets and half distracters, the participant has only a 50\% chance of making the correct selection, leading to high uncertainty. This method of eliciting uncertainty may have been biased due to the nature of the images being presented. The images used were very low resolution pictures of tanks against a generic background. This led to the potential for participants to mistake two targets or two distracters as opposites when there was no actual difference available for immediate comparison. The confound is that adding the distracters to the targets may facilitate target selection.
Additionally, the time pressure applied to this study may have contributed to differences in image processing time between scenarios. The pilot study found a mean image processing time of 1953 ms, and it was determined that three seconds would provide a high enough time pressure to elicit a workload response. By allowing the simulation to time out images after three seconds however, there is potential for ceiling effects to occur. If participants were unable to respond to the images before the time limit passed, true performance on image processing time may not have been collected. This could occur if the participant was processing a secondary task when an image was presented to them. The average amount of images which were allowed to time out through all four trials was less than nine percent, but there is still potential for image processing time to be misrepresented.

**Practical Implications**

The future of UAS operation, both abroad and within national airspace, holds many opportunities. The tasks which can be performed more safely and efficiently by an unmanned vehicle are numerous, but in order to implement the use of UAS’s for these tasks, more needs to be done to assess the capabilities and limitations of the systems. Factors that influence workload in a UAS operator need to be further understood in order to avoid performance detriments due to workload which is either too high or too low.

Time pressure plays such an integral role in determining how well a task can be performed, particularly a complex task such as UAS operation. It will be important to understand factors which increase time pressure, and be able to alleviate some of those factors, if UAS’s are to be implemented for some of the tasks for which they have so much potential. It will be necessary to understand when and how to best assist a UAS operator in order to avoid the
effects of time pressure. This is also true for the uncertainty of tasks often performed by UAS operators. An understanding of how uncertainty affects performance, as well as how it affects workload, can contribute to methods of alleviating uncertainty through things such as automated decision assistance. This study demonstrated a significant effect of uncertainty on processing times for images as well as secondary tasks. The time differences however were small enough that they may not warrant any design changes. Though statistically significant, in a practical manner, the time differences may be negligible outside of life and death situations. This is a topic which needs to be studied further, and reviewed before implementing design strategies.

**Recommendations for Further Research**

Highly autonomous vehicles, like the one simulated for this study, can open the door for one operator to supervise multiple vehicles at the same time. The workload involved with supervising multiple UAS’s is unknown, but with knowledge about the factors which influence workload with one UAS, future research can focus on implementing these factors with multiple UAS’s to determine how many vehicles one person can supervise. Future research may want to include time pressure as a factor when assessing performance while operating more than one vehicle.

There is a lot of uncertainty involved with UAS operation, due to the operator being separated from the vehicle and the environment it is in. Because of the increased level of uncertainty in UAS operation in comparison to manned flight, uncertainty is still a concept which can provide insight into performance and workload during UAS flight. The definition of uncertainty used in this study led to unexpected results, possibly due to the ability of participants to compare images directly. Future research should focus on uncertainty in a different manner in
order to provide a clearer definition of factors which contribute to it. By further understanding uncertainty when conducting UAS operations, designs can be implemented to reduce the uncertainty which contributes to higher workload and lower performance.

Conclusion

The role of UAS's within the military has grown considerably in the last decade, and can do the same within the national airspace in the near future. The capabilities of UAS's provide a much safer and efficient method for performing a number of tasks. There are still a number of concerns with regard to safety of UAS flight which need to be addressed before the full potential of this technology can be realized. The traditional method of dealing with human factors concerns, is to design the human out of the loop, and rely completely on automation. This method does not erase human factors concerns however, but merely creates new problems which must be solved. It is important to understand the human component of these systems, and be able to solve some of the issues through design which provides the ability for all components of the system to perform at optimum levels. It will remain important for studies such as this one, continue to be conducted to improve the design of UAS's in order to further the use of the technology.

This study has contributed to the knowledge of UAS operation, and the factors which may influence performance and workload within the UAS operator. Significant workload effects were shown to be elicited by time pressure, as well as effects on performance. While uncertainty still remains an area of little understanding, future research can investigate different ways to implement uncertainty in order to ascertain the effects it may have on UAS operators. It will be
important for future research to apply the findings of this study to more complex tasks involving multiple unmanned vehicles, as well as other tasks for which UAS's may prove useful.
References


Appendix A

IRB Number: 10-302

Informed Consent Form

Unmanned Aircraft System (UAS) Time Pressure and Task Uncertainty Study

Conducted by Trevor Peterson

Advisor: Dr. Dahai Liu

Embry-Riddle Aeronautical University

600 S. Clyde Morris Blvd, Daytona Beach, FL 32114

The purpose of this study is to examine the effect of time pressure and task uncertainty on performance and workload. This experiment consists of one session that will last approximately forty-five minutes. During this session, you will be asked to complete a computer-based UAS simulation trial and fill out a questionnaire regarding your perceived feeling of workload.

Your participation in this study will help us determine an appropriate level of automation and help distinguish potential pilot candidates for future UASs. There are no known risks associated with this experiment. The data collected from your participation will remain confidential. You will be compensated for your participation with extra credit in an undergraduate course and will be eligible to receive a $100.00 cash prize for best overall performance. You may terminate your participation at any time.

Thank you for your participation. If you have any questions, please ask during the experiment, or call Trevor Peterson at 970.988.9410 or Dr. Dahai Liu at 386.226.6214

Statement of Consent

I acknowledge that my participation in this experiment is entirely voluntary and that I am free to withdraw at any time. I have been informed as to the general scientific purposes of the experiment and that I will receive extra credit for participation in this study and will be eligible to receive $100.00 in the event that I have the best overall task performance in the entire study. Prize money is contingent on completion of the study.

I acknowledge that I have had the opportunity to obtain additional information regarding the study and that any questions I have raised have been answered to my full satisfaction.

I have read and fully understand the consent form and I sign it freely and voluntarily.

Participant’s Name: ________________________________

Participant’s Signature: ____________________________ Date ____________

Experimenter Signature: ____________________________ Date ____________
Appendix B

**Biographical Information Questionnaire**

<table>
<thead>
<tr>
<th>I.D.#:</th>
<th>Task:</th>
<th>Date:</th>
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*Please fill in the blanks or circle the appropriate response.*

1. What is your age? _______ years
2. What is your gender? M / F
3. Do you have normal or corrected to 20/20 vision? Yes / No
4. Are you color blind? Yes / No
5. Are you: R-handed / L-handed
6. How many hours per week do you use computers: _____ hours
7. On a scale of 1 to 5, what is your confidence level in using computers:
   
   | LOW confidence | 1 | 2 | 3 | 4 | 5 | HIGH confidence |
   |
8. On average, how many hours per week do you spend playing computer games?
   | 0-5 | 6-10 | 11-15 | 16-20 | 21-25+ |
9. What type of genre of gaming are you most accustomed to playing?
   | Action | Adventure | Role-Playing | Strategy | Simulation |
10. Have you had any other experience participating in unmanned aircraft simulation? Yes / No
11. Do you have any experience flying unmanned aircraft or remote controlled aircraft? Yes / No
   
   If so, please explain: ___________________________________________________________
Appendix C

**NASA Task Load Index (TLX) Form (Presented after the completion of each trial)**

We are interested in your subjective experience of workload. Workload is a difficult concept to define precisely, but a simple one to understand generally. The factors that influence your experience of workload may come from the task itself, your feelings about your own performance, how much effort you put in, or the stress and frustration you felt.

One way to find out about workload is to ask people to describe the feelings they experienced. Because workload may be caused by many different factors, we would like you to evaluate several of them individually rather than lumping them into a single global evaluation of overall workload. This set of six rating scales was developed for you to use in evaluating your experiences during the test trial.

Please indicate the level of workload you experienced on each of the 6 scales by circling the line at the point which best reflects the level of workload you experienced. The ends of the scales are labeled to indicate very low and very high workload. Points in between those end points represent intermediate values of workload. Please note that the Performance scale goes from Good on the left to Bad on the right. This order has been confusing for some people.

| EFFORT — How hard did you have to work (mentally and physically) to accomplish your level of performance? |
|---|---|
| Low | High |

| PERFORMANCE — How successful do you think you were in accomplishing the goals of the task set by the experimenter (or yourself)? How satisfied were you with your performance in accomplishing these goals? |
|---|---|
| Good | Poor |

| FRUSTRATION LEVEL — How insecure, discouraged, irritated, stressed, and annoyed versus secure, gratified, content, relaxed, and complacent did you feel during the task? |
|---|---|
| Low | High |

| TEMPORAL DEMAND — How much time pressure did you feel due to the rate or pace at which the tasks or events occurred? Was the pace slow and leisurely, or rapid and frantic? |
|---|---|
| Low | High |

| MENTAL DEMAND — How much mental and perceptual activity was required (e.g., thinking, deciding, calculating, remembering, looking, searching)? Was the task easy or demanding, simple or complex, forgiving or exacting? |
|---|---|
| Low | High |

| PHYSICAL DEMAND — How much physical activity was required (e.g., pushing, pulling, turning, controlling, activating)? Was the task physically easy or demanding, slow or brisk, slack or strenuous, restful or laborious? |
|---|---|
| Low | High |
NASA Task Load Index (TLX) Weighting Form

The forms you filled out included six rating scale factors that can influence workload. We are interested in your assessment of the relative contribution of these factors to your experience of workload.

People vary in their opinion of what contributes to workload. For example, some people feel that mental or temporal demands are the essential aspects of workload regardless of the effort they expended or the performance they achieved. Others feel that if they performed well, the workload must have been low and if they performed poorly, the workload must have been high. Yet others feel that effort or feelings of frustration are the most important factors in workload, and so on.

In addition, the factors that create levels of workload differ depending on the task. For example, some tasks might be difficult because they must be completed very quickly. Others may seem easy or hard because of the intensity of mental or physical effort required. Yet others feel difficult because they cannot be performed well, no matter how much effort is expended.

The evaluation you are about to perform is a technique developed by NASA to assess the relative importance of the six factors that were included in the workload rating scale in determining how much workload you experienced across all the test trials you just completed.

Below is a list of pairs of rating scale titles (for example Effort vs. Mental demand). For each pair, please circle the item that was more important to your experience of workload across all the test trials you just completed.

MENTAL DEMAND VS PHYSICAL DEMAND
TEMPORAL DEMAND VS MENTAL DEMAND
PHYSICAL DEMAND VS TEMPORAL DEMAND
EFFORT VS PERFORMANCE
PERFORMANCE VS FRUSTRATION
TEMPORAL DEMAND VS PERFORMANCE
MENTAL DEMAND VS PERFORMANCE
PERFORMANCE VS PHYSICAL DEMAND
EFFORT VS FRUSTRATION
TEMPORAL DEMAND VS EFFORT
EFFORT VS MENTAL DEMAND
PHYSICAL DEMAND VS EFFORT
FRUSTRATION VS TEMPORAL DEMAND
MENTAL DEMAND VS FRUSTRATION
FRUSTRATION VS PHYSICAL DEMAND