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Developing Human-Machine Interfaces to Support Monitoring of UAV Automation

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Developing Human-Machine Interfaces to Support Monitoring of UAV Automation

Final Contract Report

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Abstract

Unmanned Aerial Vehicles (UAVs) are rapidly becoming an integral part of contemporary military operations. In light of developments in UAV flight and payload technologies, the role of UAV operators is evolving into that of supervisory controller of complex automated system. However, it is well established that human operators perform poorly in this role. A growing body of literature points to the crucial role that trust in automation plays in determining the efficacy of human monitoring of automated systems. A recent compilation of research on trust in automation suggest that providing operators with information related to automation process and context-specific automation reliability is essential in promoting appropriate trust in automation.

This report presents a research plan to create innovative design concepts for cognitive artifacts that communicate these two types of information to UAV operators for the purpose of engendering appropriate trust in automated systems. It includes a categorization of the emerging automation technologies in UAV systems, an analysis of the changing tasks of UAV crews, and a selective review of relevant human-automation research. The report then introduces two human-machine interface concepts for selected types of UAV automation and proposes a research plan for testing and evaluating these design concepts.

Executive Summary

This article presents an experimental plan for the evaluation of theory-driven human-automation interface concepts in the domain of Unmanned Aerial Vehicles (UAVs). The experiment is motivated by the evolution of UAV technology towards more highly automated systems and the relegation of human operators to the role of supervisory controller. Humans have consistently demonstrated themselves to be ill-suited for this role; thus, we anticipate that future UAV systems will be susceptible to human-automation breakdowns leading to mission failures.

In an attempt to head off such failures, human factors researchers are exploring the role of human trust in automation as a means of managing the uncertainty inherent in mixed-initiative systems. A recent comprehensive review of the trust literature yields design guidelines for engendering appropriate levels of trust in automation. We followed these guidelines to produce example interface artifacts that show information about the automation process (i.e., the automation algorithm) and relevant context information that affects the automation's behaviour.

We propose an outline for a simulator study to evaluate these interface concepts with human operators. The study casts UAV operators opposite sensor fusion automation that identifies targets based on analysis of multiple sensor images. The task of the joint human-automation system is to correctly identify friendly and hostile military targets in a scene. The UAV operators will be assigned to four groups to test the differential effects of providing information about automation context and process. We hypothesize that providing either or both of these types of information about automation will engender more appropriate trust in the automation and lead to performance improvements over a control condition lacking this information. The results would constitute a unique and substantial contribution to both the human-automation interaction literature and to the ongoing development of UAV automation.

Introduction

Unmanned Aerial Vehicles (UAVs) are rapidly becoming an integral part of military operations, serving mission-critical roles previously allocated to vehicles operated by humans [21]. Many of these missions are of the "dull, dirty and dangerous" variety[1] [1] where supplanting a human operator with a machine is welcome on many levels. However, anticipated developments in UAV flight and payload technologies suggest that the role of the UAV operator is evolving into that of a supervisory controller of a complex system [9], a task for which the human is ill-suited.

Two characteristics of complex systems that challenge human operators are uncertainty and automation[2]. Uncertainty refers to the inevitable incompleteness of sensed data. This could be a function of an absence of sensors, limitations in sensor fidelity, impairment by environmental conditions, or degradation in sensor performance over time. The result is that the human operator can never know the true state of the world, and her impoverished view of the world will rarely match that of any other actor. Automation, in effect, serves as an additional actor in complex systems. To varying degrees it acquires, analyses, makes decisions about, and acts on its own impoverished set of sensed data. One of the many extraordinary challenges of human interaction with complex systems is supporting human-automation interaction in the face of uncertainty.

A key insight into addressing this challenge is that human reactions to computers under uncertainty parallel interpersonal reactions under similar conditions. Trust is the attitude that another agent (be it human or machine) will act to achieve a person's goals in uncertain situations [24]. This attitude plays a major role in guiding the decision to rely on that agent. For this reason, human-automation trust has emerged as a central human factors research theme. And because human-automation interaction occurs through cognitive artifacts (e.g., training, procedures, decision support systems, human-machine interfaces), it is imperative that these artifacts be designed to engender appropriate trust in automation under uncertainty.

While the design goal is clear, there is very little consensus in the human factors community regarding which cognitive artifacts hold the most promise for supporting human operators performing supervisory control. Moreover, these are competing approaches designing these artifacts. For example, various researchers have proposed design guidelines for human-automation interfaces [7][24]. To date, there has been no direct empirical study of any of these sets of guidelines[3].

We thus observe in the UAV domain a confluence of changing roles for human operators and a scarcity of disciplinary understanding of how to support humans in that role. Specifically, we anticipate that UAV operators will increasingly be faced with the challenge of supervising complex automation that is susceptible to uncertainty and we recognize that empirical support

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[1] "Dull" referring to extended missions with low event rates (e.g., patrolling a 'no-fly' zone); "dirty" referring to missions undertaken in environments that are not conducive to healthy or safe operation (e.g., chemical and biological agent-sensing); "dangerous" referring to missions that expose aircraft and aircrews to hostile enemy action (e.g., air defence suppression).

[2] Vicente [41] lists eleven characteristics of complex systems: Large problem spaces, social dynamics, heterogeneous perspectives, spatial, distribution, dynamic system response, hazard, coupling between subsystems, automation, uncertainty, mediated interaction, and disturbances. Clearly more than uncertainty and automation are present in UAV operations. We focus on these two to narrow our problem.

[3] This is not to say that there have been no empirical evaluations of human-automation interface concepts. Rather, none of the interface concepts evaluated appear to have been the direct product of theory-driven design guidelines.

for theory-driven design guidance is effectively absent. The goal of the proposed research is to apply Lee and See's [24] guidelines for the design of information about automation for the purpose of engendering appropriate trust in that automation. Towards that end, this report:

1. Discusses the changing tasks of UAV crews,
2. Categorizes UAV automation and some of the ways that uncertainty manifests therein,
3. Reviews contemporary UAV human-automation research,
4. Introduces two human-machine interface concepts for selected types of UAV automation, and
5. Proposes a research plan for testing and evaluating those design concepts.

UAV Work Domain

UAV Sensor Payload

Table 1 summarizes some characteristics of the two most prevalent sensors used in current UAV systems. Although other sensors are in use and more are forthcoming, these will suffice for our current purposes.

Table 1. Summary of Sensor Characteristics

Sensor	Characteristics
EO/IR	An electro-optic/infra-red (EO/IR) camera [6] provides both optical and infrared photographic imagery. Digital enhancement enables further sharpening of images. IR sensors can detect heat sources but cannot spot vehicles or aircraft on the ground once their engines are cold. They are also unable to penetrate clouds and darkness and are only slightly less likely to be fooled by camouflage. IR sensors can also be fooled by dummy heat sources and can be blocked to some degree by special IR-netting. In addition the UAV camera output is not appropriate for wide area search and monitoring because of its narrow field of view.
SAR/MTI	Synthetic Aperture Radar (SAR) uses microwave signals to provide all weather, day/night imagery of terrain features and man-made objects. The sensor also provides range and bearing information. However, the resolution of SAR imagery is inferior to that of EO/IR and requires a higher level of skill to analyze. SAR images are also subject to noise caused by unfavorable conditions such as rough seas or large, metallic surfaces. In addition, the radar system is also susceptible to jamming. One drawback of SAR is that it only shows the position of stationary targets. Moving Target Indicator (MTI), in contrast, uses radar to show only targets that are in motion.

Crew Complement and Task Allocation

When we refer to a UAV, we are referring to a system [1]. A fully operational UAV system consists of one or more aircraft, a payload of sensors and/or effectors, a control station, and a data communications architecture. Also included in that system is a crew of human operators with various roles depending on the UAV system, mission, nationality, and service branch.

A US Defense Department road map for UAVs [30] lists the training programs for several UAV systems, thereby identifying crew complement and roles for each system. Although these differ across platform, it is sufficient for our purposes to characterize common features of UAV crewing.

Generally speaking, a contemporary UAV crew consists of a pilot (also known as an air vehicle operator) and one or more sensor (or payload) operators and a mission planner or tactical navigator [23] [39]. The pilot is responsible for flying the UAV, sometimes using traditional stick and rudder controls and at other times by engaging an autopilot or waypoint fixing [23] [30]. The sensor operators are responsible for manipulating sensors, optimizing them for data collection, and interpreting the data collected [39]. For example, an operator might select and tune a sensor to locate a target through cloud cover, identify the target, and communicate its location and identity to other assets in the battlespace. The tactical navigator acts as the mission commander, and is responsible for managing the use of available resources (including multiple UAVs and the control station itself) to accomplish the mission goals [39].

Although human factors research in UAV operation is beginning to pick up speed, there are few publicly available analyses of UAV operator tasks. Perhaps the best source is a cognitive task analysis performed by Gugerty et al (1999) based on interviews with UAV crews. They present a goal hierarchy for a typical Predator mission (see Figure 1). The analysis shows the emphasis on reconnaissance missions and the particular difficulties involved in re-planning missions. However, there is little treatment of automation in the analysis, perhaps because, at the time that it was completed, few of the crew tasks were automated.

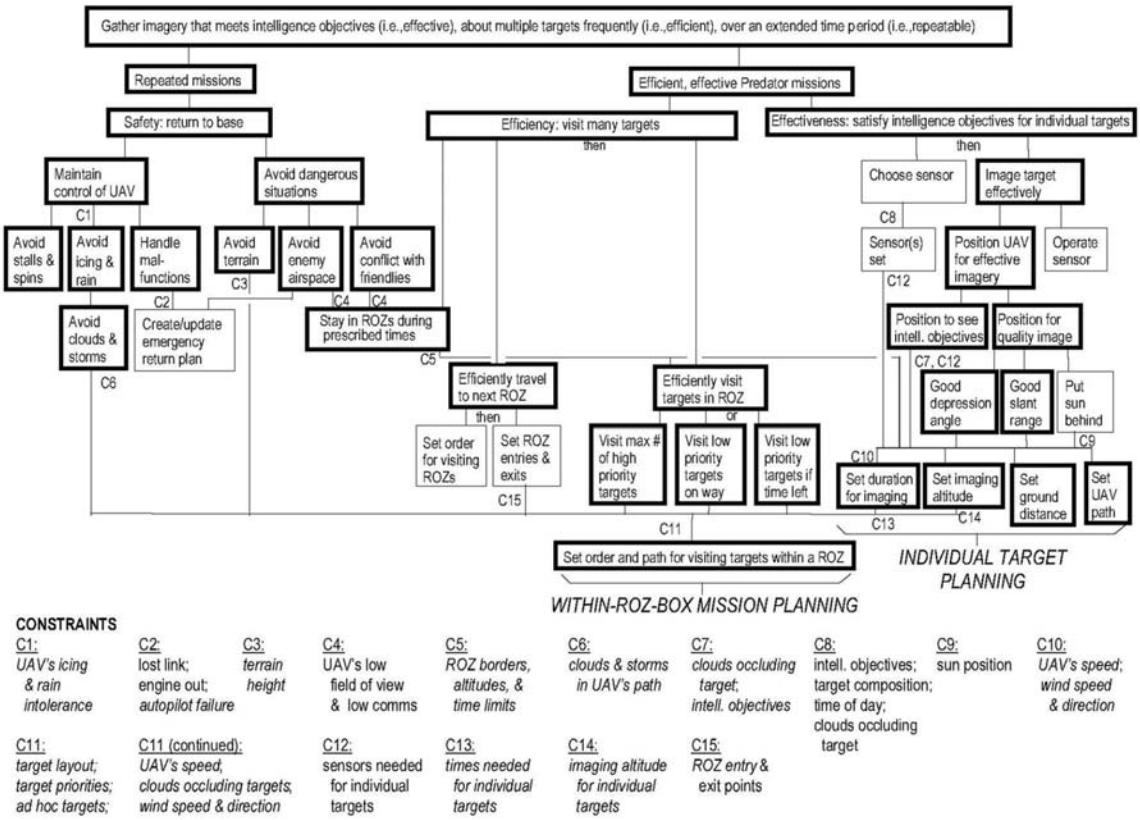

Figure 1. Goal hierarchy for a Predator mission.

A clearly defined future goal for UAV operations is to reduce the ratio of operators-to-aircraft by having operators serve multiple roles [45]. The anticipated means of achieving this is through automation. The first role that is likely to be assigned to automation is flight control. Operators of future UAV systems are envisioned to issue navigation waypoints with flight paths planned and executed by automation. Tasks that are currently allocated to the sensor operator and tactical navigator will also become more automated. Automated target recognition and data fusion algorithms are expected to relieve the sensor operator of much of the information analysis burden, presenting him with conclusions to verify and courses of action to approve.

Unfortunately, we have not identified any task analyses of operations of more highly automated UAVs. Moreover, we have not had direct access to any subject matter experts to conduct our own analyses. Therefore, many of our assumptions about the future role of UAV operators are drawn from sources that promote UAV technology without direct consideration for human factors issues. The clear implication of these sources is that the task of the future UAV payload operator in particular will be increasingly one of monitoring automation processes.

This foresight should raise warning flags with human factors engineers. Elsewhere in aviation [3] and in other domains [47], advances in automation technology have frequently failed to deliver the expected improvements in system performance. These failures are often attributed to poorly designed human-automation interaction. There is a sense in that human factors community that UAVs may be a domain where we can make an impact on the design of future UAV systems to head off human-automation interaction problems.

Automation Categories

Emerging automation technologies in UAV systems fall into several categories [40]:

1. Sensor Fusion: integrating information from various sensors.
2. Communications: handling communication and coordination between multiple agents in the presence of incomplete and imperfect information.
3. Flight Path Planning and Trajectory Generation: determining an optimal path and enabling control maneuvers to allow a vehicle to meet objectives and respect constraints such as no-fly zones.
4. Task Allocation and Scheduling: determining the optimal distribution of tasks amongst a group of agents, with time and equipment constraints.
5. Cooperative Tactics: formulating an optimal sequence and spatial distribution of activities between agents in order to maximize chance of success in any given mission scenario.

In many situations, these types of automation will interact. For example, motion planning and cooperative tactics automation will determine the path of the UAV, and therefore influence the information acquired from sensors.

Selection of Sensor Fusion Automation

The current research goal is to develop human-automation interfaces that assist UAV operators supervising less than perfectly reliable automation under uncertainty. We are particularly interested in how environmental context may influence the automation performance in specific situations [2] [7] [28]. Sensor fusion automation appears to fit our requirements:

- The output of the sensor fusion automation typically includes a degree of uncertainty [46], providing a list of possible target types and their probabilities.
- Sensor fusion automation is not perfectly reliable. Efforts to improve sensor fusion algorithms are underway [19], [29] and [46], but the technology is still relatively immature.
- Sensor fusion automation is limited by incomplete and noisy raw data collected by the sensors, often as a result of environment conditions. For example, cloud cover, dust and smoke interfere with many sensors. As well, the data link may be lost due to obstacles between the UAV and the control station [39]. Finally, adversaries may employ countermeasures to degrade the quality of data collected [29].

Sensor Fusion Algorithm Example

Sensor fusion automation aggregates data from multiple sensors to support target detection, target identification and tactical decision-making. An application of Dempster-Shafer theory provides a good example of sensor fusion automation [46]. The inputs to this sensor fusion automation are two lists of possible target types and possibilities provided by independent automatic target recognition (ATR) systems. Each ATR system processes a sensor image and passes its assessment of targets in the scene to the sensor fusion automation[4].

The fusion algorithm is built on Dempster-Shafer theory; a mathematical theory of evidence used to combine independent pieces of information (or evidence) to find the probability of a hypothesis. Some basic concepts in Dempster-Shafer theory follow. A *frame of discernment* (θ) is defined as the universal set of all propositions being considered. For example, consider the case of identifying whether an object is a T34 tank. The frame of discernment contains the following propositions:

- $\{T34\}$: the object is a T34 tank
- $\{\neg T34\}$: the object is not a T34 tank
- $\{T34,\neg T34\}$: it is inconclusive whether or not the object is a T34 tank (this is called the "ignorance set")

Each proposition in this set can be assigned a *degree of belief* (the function Bel) based on the reliability of sensor data. As an example, suppose sensor data determines an object to be a T34 tank. The probability that the sensor is reliable is 0.8 and the probability that it is unreliable is 0.2. These probabilities justify a degree of belief of 0.8 that the object is a T34. However, the degree of belief that the object is *not* a T34 is 0, which means that no evidence has led to the possibility that the object is not a T34. Intuitively, this makes sense because the detection algorithm does not explicitly test whether an object *fails* to be a T34. Note that a zero degree of belief is different from a zero probability, which would mean that there is no chance that the object is a T34. Mathematically, the degree of belief in this example can be represented by:

- $Bel(\{T34\}) = 0.8$
- $Bel(\{\neg T34\}) = 0$
- $Bel(\{T34,\neg T34\}) = 0.2$

This simple example illustrates how the degree of belief for one hypothesis ("Is the object a T34 tank?") can be obtained using one item of evidence. Obtaining the belief function from multiple

[4] As the name implies, ATR is automation itself so this example is one of coupled automation.

sets of uncertain evidence (e.g., acquired through multiple sensors on the same UAV, multiple sensors on different UAVs, or multiple instances from the same sensor at multiple times) is more complicated.

For example, assume that UAV sensors on the battlefield scan an area of terrain and output a list of candidate identities for each target (T34 tank, M12 tank, etc.) with their respective confidence levels. The identity with the highest confidence level initially determines the active frame of discernment, although this may change once additional evidence is added. These frames of discernment can disagree: one sensor may indicate that the target is most likely a T34 tank, while another may indicate that it is probably an M12 tank. Multiple candidate lists can be "fused" to produce an aggregate belief function for all potential target identities. To do this, a *confusion set* is formed for each list by taking all members above a confidence level threshold σ. The belief function for a frame of discernment

Any two confusion sets S_1 and S_2 are fused according to one of three scenarios:

1. S1 and S2 have the same active frame of discernment (i.e. the identity with the highest confidence level in each set is the same). The belief functions of the two sets are fused according to Dempster's rule of combination (not described here).
2. S1 and S2 have different frames of discernment, with some shared members. The single member with the highest confidence level in either set is chosen to be the active frame of discernment (say this is I1 in S1). If I1 is not in the other list, we use the belief function of S1 as the result. Otherwise, we combine the belief functions of both sets for I1.
3. S1 and S2 have different frames of discernment, with no shared members. No combining occurs, and we use the belief function for S2.

The general idea in the algorithm presented by Yu, et al. (2004) is to obtain belief functions from the confidence levels outputted by ATRs. The belief functions can then be fused and refined as additional evidence is collected.

Analytical Redundancy

The principle of analytical redundancy suggests that providing information on the context of the automation in the interface can allow an operator to more easily identify the exact source of erroneous or unreliable automation. An interface in the UAV sensor domain can incorporate analytical redundancy by displaying the signals from all elements in the system, as shown in Figure 2. The output of the UAV sensor is an image of the field. This data is processed by an Automatic Target Recognition (ATR) system, which outputs a list of candidate identities with respective confidence levels. In the information aggregation stage, confusion sets are determined based on a threshold σ and belief functions are calculated. These sets are fused and the aggregate belief function is outputted.

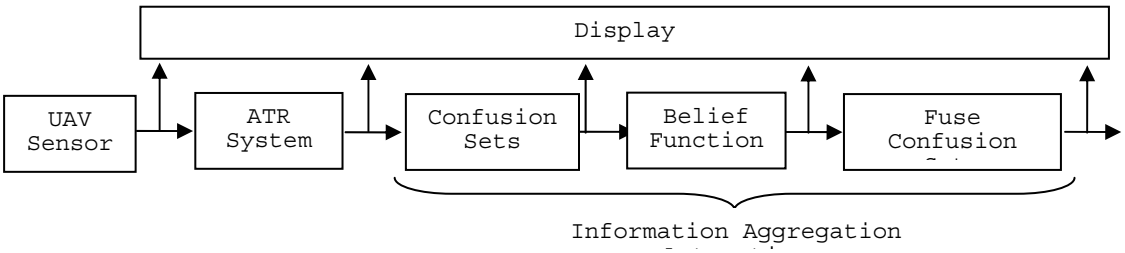

Figure 2: Generic UAV sensor fusion automation.

Human-Automation Interface Concept 1

The display shown in Figure 1 supports analytical redundancy by revealing information about the input and output signals to every element in the UAV sensor system. Moreover, it provides the operator with a description of how the automation performs information aggregation by displaying information at the intermediate steps of the belief function, the confusion sets and fusion of the sets. We believe that this satisfies the design guidelines for process information as described by Lee & See (2004). The theory-driven design framework predicts that providing this information will help the operator to isolate any errors in the system and establish an appropriate level of trust in the automation.

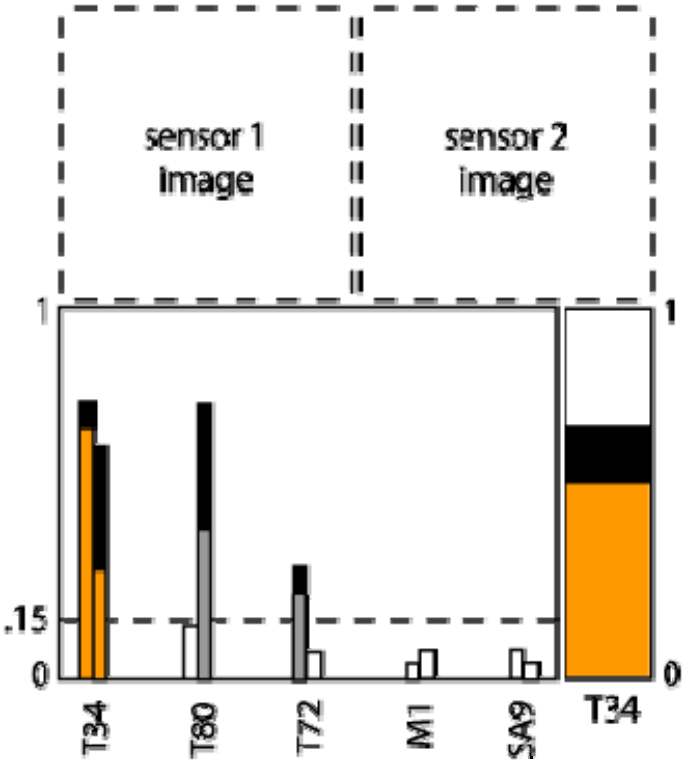

Figure 3: Cognitive Artifact Concept #1 for information aggregation based on Dempster-Shafer theory

The main elements in this interface concept are sensors images (top), candidate list graph (bottom left), and active candidate graph (bottom right). The sensor images are the output signals from the UAV sensors (two are assumed in this case), which show the ground area hypothesized to contain a tank.

The candidate list graph contains information on each sensor ATR's candidate list with respective confidence levels represented by the height of each non-black bar. In this example, the stacked columns on the left corresponds to sensor 1 and the columns on the right corresponds to sensor 2. Confusion sets are determined by applying a threshold $\sigma = .15$ (indicated by the dotted line). Members which are not part of any confusion set are white to reduce their visual presence. The belief function is calculated for each member "T" contained in the confusion sets and displayed in the following manner:

- Bel({T}) is coloured orange if it is the active frame of discernment, and grey otherwise
- Bel({¬T}) is coloured black
- Bel({T,¬T}) is not shown (its value corresponds to the "missing" space)

The active candidate graph provides a visualization of the aggregate belief function after fusion of the confusion sets, and corresponds to the active frame of discernment. It follows the same colour scheme as the candidate list graph, such that the operator can easily identify the active frame of discernment in both graphs.

An example where this interface concept can be applied is for a UAV that has one SAR sensor for stationary object identification and one MTI sensor for moving object identification. Both sets of sensor data generate independent candidate lists, but one may be more reliable than the other under certain conditions (e.g., climate, UAV altitude, time of day, prior knowledge that the object is stationary or moving). The operator can isolate one sensor's belief function in cases where the aggregate belief function is likely to provide misleading results.

Human-Automation Interface Concept 2

The second interface concept, shown in Figure 4, also incorporates analytical redundancy by revealing information about all signals in the UAV sensor system and by displaying information at the intermediate steps of the automation.

The main elements in this interface concept are sensor images (top) and a candidate list gauge (bottom). Information from Concept #1's candidate list graph and active candidate graph are incorporated into a single interface element, the candidate list gauge. As in Concept #1, the sensor images are the output signals from two UAV sensors, showing the ground area hypothesized to contain a tank.

The candidate list gauge contains information on each sensor's candidate list with respective confidence levels represented by triangular markers pointed toward a value on the gauge line. Sensor 1 data corresponds to orange markers with the number "1" while sensor 2 data corresponds to green markers with the number "2." As in Concept #1, confusion sets are determined by applying a threshold $\sigma = .15$ (indicated by the dotted line in the upper section of the gauge). The gauge is vertically split in the middle, with values for Bel({T}) above the zero line and values for Bel({¬T}) below the zero line (for each candidate T). Note that Bel({¬T}) values are only computed for candidates belonging to confusion sets. Bel({T,¬T}) is not shown, although its value can be inferred.

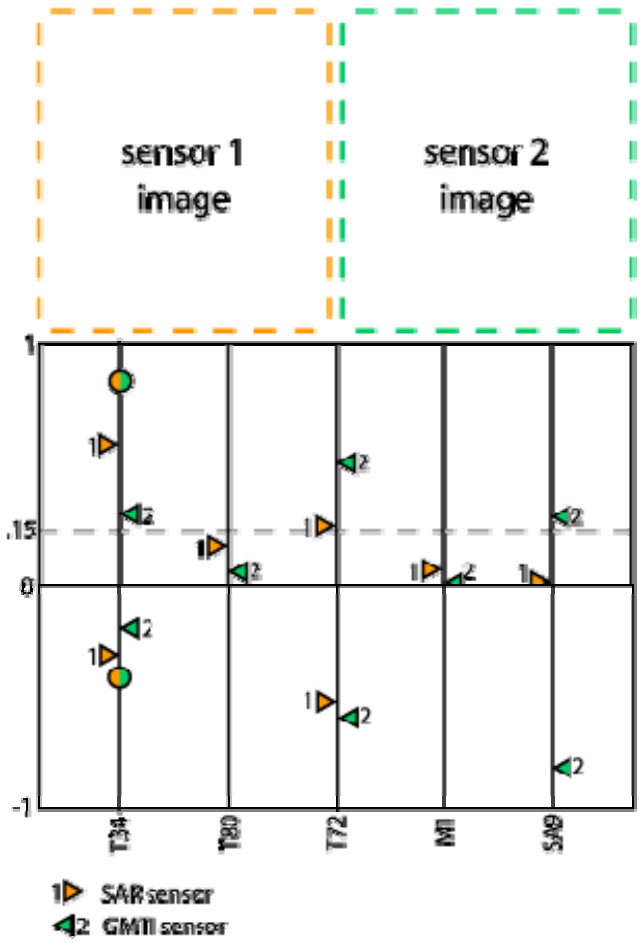

Figure 4: Cognitive Artifact Concept #2 for information aggregation based on Dempster-Shafer theory

The candidate list gauge provides a visualization of the aggregate belief function for the active frame of discernment, the value of which is represented by the position of a circle. The circle interface element also indicates how the confusion set information is fused as shown in Figure 5.

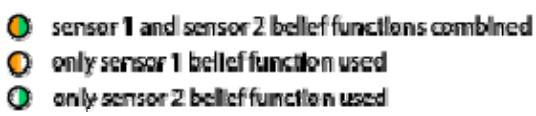

Figure 5: Fusion of confusion set information indicated by the circle interface element

As in Concept #1, this interface concept allows the operator to distinguish the confidence levels obtained from each sensor, by looking at either colour of the triangular marker or the number beside it. This separation is of value when one sensor is known to be more reliable under certain environmental conditions. The interface also allows the operator to easily identify the values for Bel({T}) and Bel({¬T}), above and below the zero line respectively. Presenting the aggregate belief function in the gauge allows the operator to directly compare the component effects of each sensor's belief function.

Comparison of Human-Automation Interface Concepts

The two concepts presented here are initial low-fidelity prototypes that have not undergone any evaluation. Before they are included in a research study, they should be subjected to both

feasibility and usability analyses. Such analyses are included in a research plan below, but will not be detailed here.

Current Research in UAV Automation

UAVs are quickly becoming the domain de jure for human factors research for at least four reasons. First, the wide range of UAV operator tasks allows for many types of behavioral research. Second, the applicability of UAVs across a broad range of military (lethal and non-lethal) and quasi-military (e.g., intelligence gathering, border security) operations aligns with a similarly broad range of government funding sources for research and development. Third, cases for civilian application (e.g., law enforcement, forest-fire fighting) are plausible enough to classify the technologies as dual-use. Finally, UAVs offer the allure of aviation without the required domain expertise that comes with piloting.

For these reasons, a host of UAV research programs are emerging to explore a range of research issues. This trend suggests two likely benefits for near-term human factors research. First, we can be optimistic that a well-conceived research program couched in the domain has a reasonable chance of securing sustaining funding[5]. Second, we can be optimistic that such a program will also find outlets for its results in quality industry and academic journals.

Synthetic Environments and Tasks in UAV Research

In this section, we review the experimental environments currently in use in UAV human factors research. The review for each research programme includes:

- a description of the synthetic task environment,
- an account of the tasks allocated to the human operators,
- a characterization of the type of automation employed

This review contributes to the current work in two ways. First, it will establish requirements for a 'state of practice' synthetic environment that can provide valid findings regarding the theoretical issues to be investigated. Second, the review will help to identify the tasks of UAV crews that we may wish to emulate. Detailed descriptions of such tasks are scarce in the available literature and we have not been afforded the opportunity to conduct a task analysis with subject matter experts. The synthetic tasks used in the reference literature, while artificial, are systematically abstracted from corresponding real-world tasks by other human factors practitioners [23]. Therefore, we have some confidence that this literature can help to overcome our knowledge deficiency with respect to real-world UAV operator tasks.

Dixon, Wickens, et al.

Institute: University of Illinois Institute of Aviation, Aviation Human Factors Division

References:

[14] [15] [16] [17] [43]

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[5] Assuming that the program is carried out in a jurisdiction eligible to access those funding.

Synthetic Environment

A series of studies on human interaction with UAV automation have been conducted using a UAV synthetic task environment. VEGA[6] was used as the overall graphical scene controller [see Figure 6]. The interface was displayed on a 19-inch monitor with 1280x1024 resolution. The interface (see Figure 6) was divided into four view ports with four dedicated process views:

- 3-D visual image display with two modes:
  - fixed viewing angle and zoom in 'tracking' mode, and
  - variable viewing angle and zoom in 'loitering' mode
- 2-D navigational display
- system gauges for monitoring for system failures, and
- message box to receive instructions

The control devices include a digital 3D joystick and an X-Key 20-button keypad. The joystick is used to manipulate the UAV and the camera while the keypad is used to indicate responses.

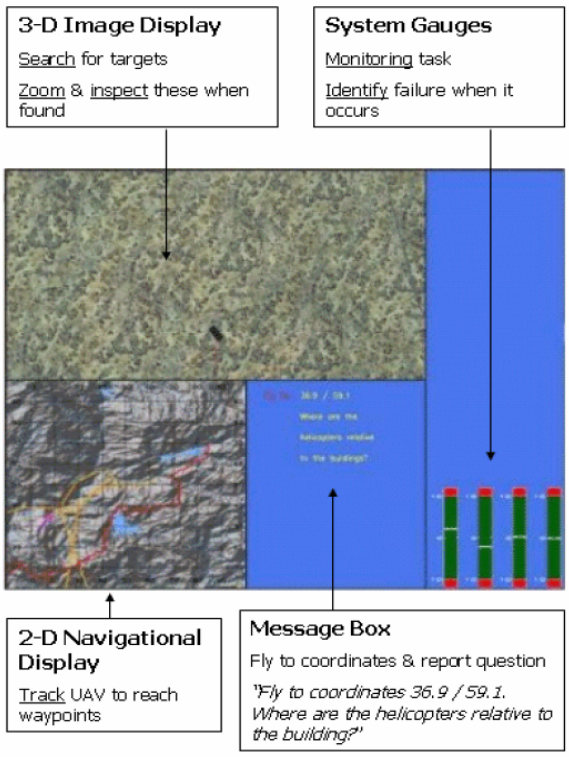

Figure 6. The UIUC synthetic experiment environment (from [15]**)**

[6] A software application development designed for the creation and deployment of real-time 3D simulation, training, and visualization applications.

Synthetic Tasks

Undergraduate and graduate students were asked to fly one UAV through several mission legs, while completing three main tasks:

1. Mission Completion: subjects were tasked (via the message box) with traveling to map locations to perform a target inspection and reporting task.
2. Target Search: in between map locations, subjects were tasked with detecting and reporting low visibility targets of opportunity. These targets were camouflaged and their occurrence and location were unknown to participants. Moreover, they were much smaller than those in the mission completion task.
3. System Monitoring: when a system gauge went "out of bounds", participants had to press a button to detect the system failure, indicate which gauge had failed, and then report the current location of the UAV. The detection and acknowledgement sub-task appears to be taken from the Multi-Attribute Task (MAT) battery.

The measurements taken in these experiments include the objective performance in different tasks as well as some subjective ratings, such as trust. Trust was assessed by questionnaire; for example, "How do you assess the trustworthiness of the auto-pilot?" ([15], pp.64)

Automation

The studies have examined several types of pilot interaction with perfect and imperfect automation. Each of the three tasks above can be assigned to the participant or to automation aids. The target detection automation was designed to provide an auditory signal when it sensed a target of opportunity in the 3-D image display. However, it did not designate the specific location of the target.

Ruff, et al.

Institute: Air Force Research Lab, Human Effectiveness Directorate & Sytronics, Inc.

References:

[37]

Synthetic Environment

The purpose of the research is to investigate the human factors in supervisory control of multiple UAVs. It used the Multi-Model Immersive Intelligent Interface for Remote Operation (MIIIRO) test bed, which is described as "a generic UAV operator interface simulation testbed" ([37], pp. 218). The MIIIRO workspace consists of two monitors as shown in Figure 7. The tactical situation display on the left shows the UAV routes, suggested route re-plans, waypoints, targets, threats, and unidentified aircraft. The image management display on the right shows camera images taken by UAVs with hostile targets highlighted by an automatic target recognizer (ATR). Below the image is an image queue. The control devices are a keyboard and a mouse.

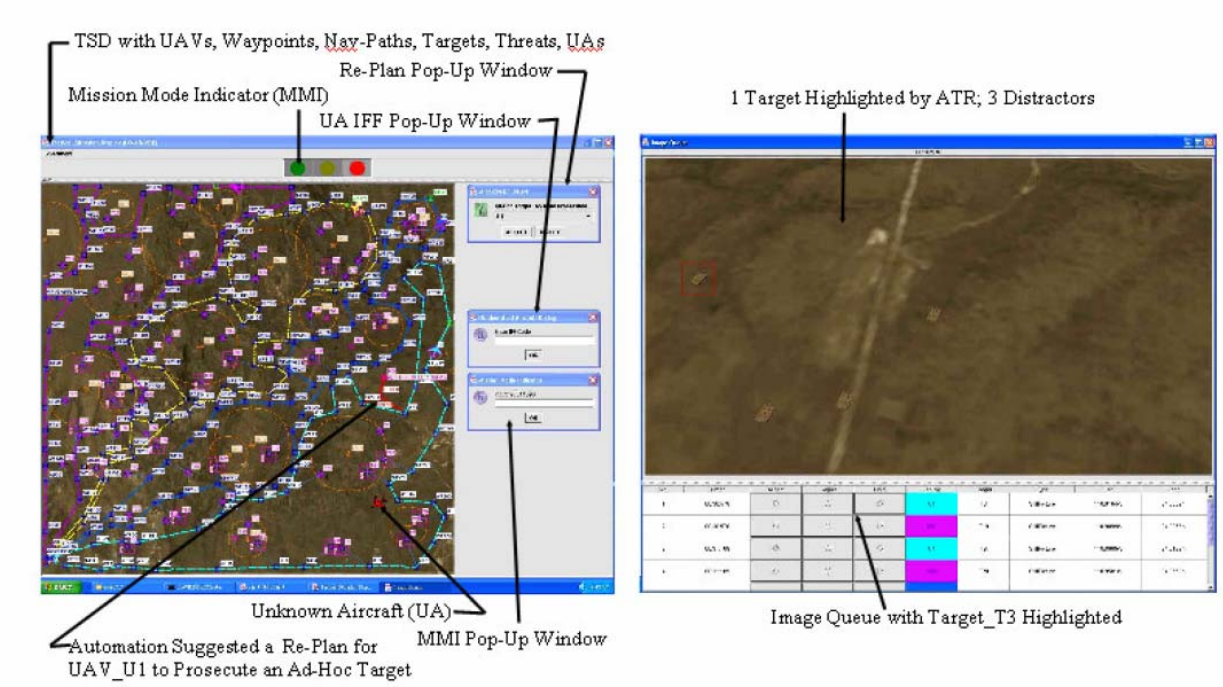

Figure 7. The MIIIRO synthetic task environment: Tactical Situation Display (left) and Image Management Display (right) (from [37])

Synthetic Tasks

Participants (whose characteristics were not mentioned) were required to complete to four prioritized tasks:

1. Respond to a highly unexpected, non-routine, high-priority event.
2. Accept/reject route replanning solutions suggested by automation in response to unanticipated targets and threats.
3. Accept/reject automated target identifications.
4. Acknowledge changes in mission mode.

The measurements taken from the experiments [37] include the time and accuracy in each task, subjective rating of task difficulty, workload, trust, automation and self-confidence. The approaches for soliciting subjective rating were not mentioned in the paper.

Automation

Two kinds of automation were employed, automatic route planning and automatic target detection. For both automated systems, the reliability and automation level (management-by-consent vs. management-by-exception) served as independent variables.

Cooke, et al.

Institute: New Mexico State University's, Cognitive Engineering Research on Team Tasks (CERTT) Laboratory

References:

[9][10][11][12]

Synthetic Environment

CERTT's UAV-STE simulates the ground control operations of a UAV. The interface allows users to navigate the UAV to a position and perform a reconnaissance task of photographing designated targets. CERTT uses the setup to study team cognition with experiments involving a three-person team.

The experimental set-up is composed of four participant consoles and one experimenter control station, as shown in Figure 8 and Figure 9.

Figure 8: Participant consoles

Figure 9: Experimenter Control Station

Each participant console contains the following: two computers, one monitor, headsets and an intercom. Each team member has a separate role, either Air Vehicle Operator (AVO), Payload Operator (PLO), or Tactical Navigator. Their respective displays are shown in Figures 3-5.

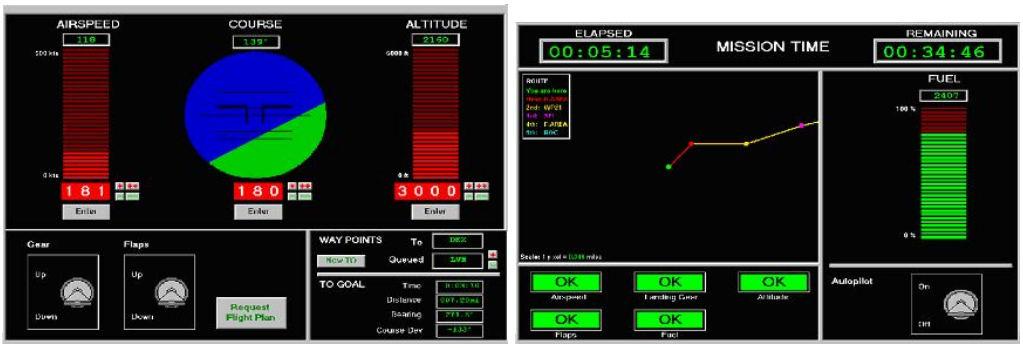

Figure 10. Screenshots of AVO display.

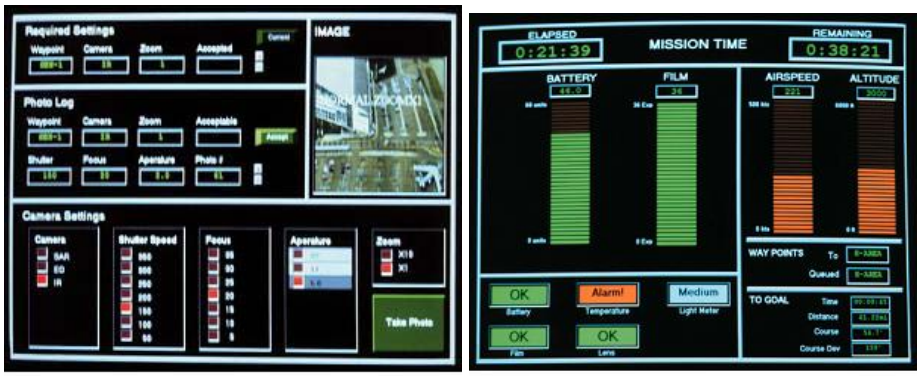

Figure 11. Screenshots of PLO display

Figure 12. Screenshots of Tactical Navigator display

The STE is Windows-based and implemented through user-defined objects developed in the Rapid™ Development Environment. The setup involves a combination of custom-built and off-the-shelf hardware.

Synthetic Tasks

This STE is used to study UAV operations and team coordination. The individual responsible tasks for each operator are shown below. However, to fulfill the mission, they have to coordinate in order to maneuver their UAV.

- Air vehicle operator: controls UAV airspeed, heading, and altitude and monitor air vehicle systems.
- Sensor operator: control camera settings, takes photos, and monitors camera systems.
- Tactical navigator: navigator, mission planner, plans route from target to target under constraints.

In the experiment, Cooke, et al. (2000) recruited 108 New Mexico State University students in the experiment. Outcomes, team process behaviors, tam situation awareness, taskwork knowledge and teamwork knowledge were measured in the experiment. Outcome included mission completion rate, time to complete mission, and experimenter ratings of team performance.

Automation:

Automation settings are not mentioned in the papers.

Prabhala, et al.

Institute: Russ Engineering Center

References:

[35]

Synthetic Task Environment

Rather than describing a research program, this article describes the development of a UCAV synthetic task environment for human factors studies of multiple UAV control. This synthetic task environment consists of interface software developed in VEGA and simulation software developed in JAVA. A screenshot of the interface is shown in Figure 13. A status panel and control panel are layered at the lower part of the interface, and a map display is shown on the upper part. The map display is further divided into three different view ports: satellite view, camera view and following view. The interface is displayed on a 21 inch monitor, and input devices include a mouse, keyboard and voice [35].

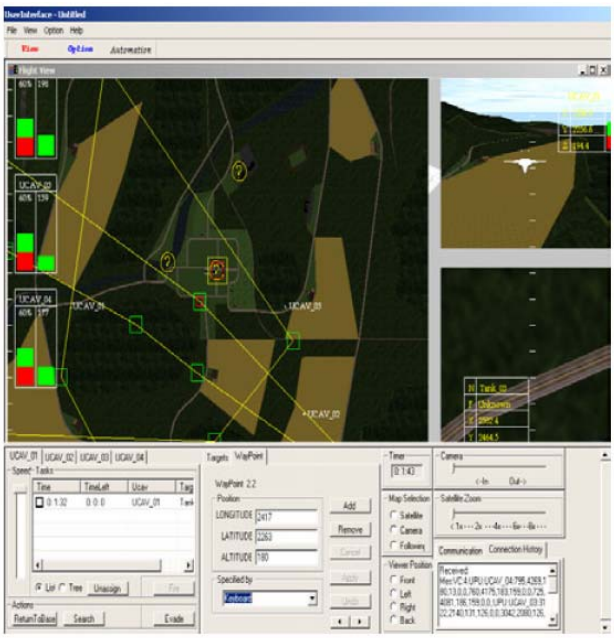

Figure 13. Screenshot of the human controller interface (from [35])

Synthetic Tasks

The interface and simulation design was driven by a suppression of enemy aerial defenses mission. Therefore, the synthetic task environment has mechanism to support various tasks in control of UCAV, including: "navigation, flight paths, UCAV updates, target tracking, target identification, target destruction, and elements that aid the UCAVs" ([35], pp. 1036). In a typical UCAV operation scenario, the operator would complete the following tasks:

1. System Monitoring: monitor and control the UCAVs for unanticipated variability.
2. Route Planning: make adjustments to the flight paths to detect, identify and destroy target and return to base.
3. Target Detection & Identification: detect and identify targets via simulated sensors.
4. Target Destroy: select the right kind of ammunition to engage different types of target.

Automation

Based on the description provided in the paper, the UCAV waypoint tracking and target acquisition are automated. The target acquisition serves as an example of sensor fusion automation. A simulated long-range sensor detects targets while a second, short-range, sensor identifies the targets. No explicit information is provided about the automation in the interface.

Bush, L.

Institute: MIT Lincoln Laboratory

References

[5]

Synthetic Task Environment

The purpose of this research [5] is to study how cueing data from Moving Target Indicator (MTI) automation can be communicated to a Predator UAV camera operator. The synthetic task environment simulates the Predator UAV user interface. The user interface is displayed on two monitors, the left one shows the simulated UAV video, the right one shows a situational awareness map. The cues generalized by the MTI algorithm are highlighted on the situational awareness map with red dots.

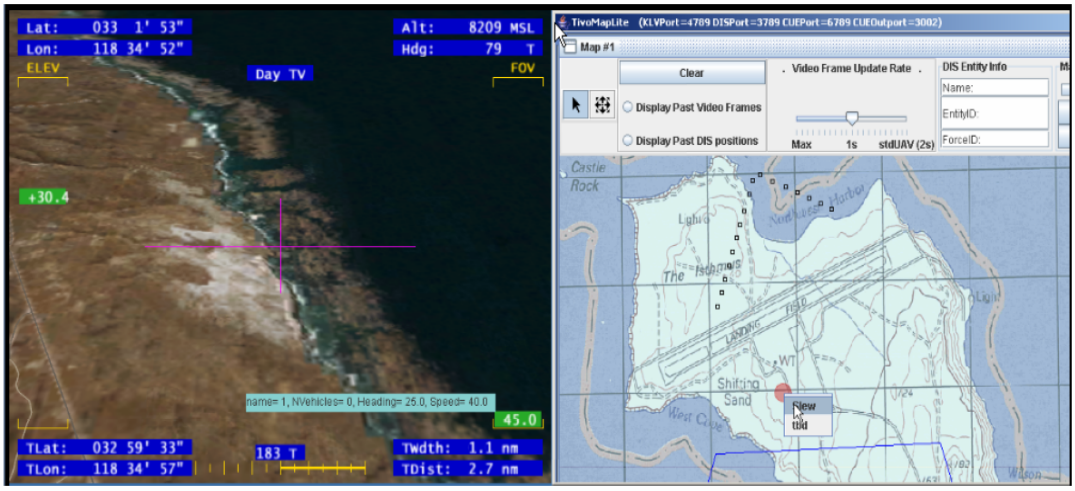

Figure 14. Screenshot of the synthetic task environment: Simulated UAV Video (Left), MTI Cue & Situational Awareness Display (right) (quoted from [5])

Synthetic Tasks

The task designed for future experiments is to collect battlefield convoy information. This task involves selecting a cue, directing the UAV video sensor to collect the information from the cued location, searching for and identifying the convoys, counting the number of vehicles in convoys and acquiring an image of them [5].

Automation

The automation algorithm studied in this research utilizes the information from MTI Radar to predict the location and activity of convoys.

Summary of Findings Regarding UAV Research

1. The synthetic task environments employed in current human factors UAV research domain are generally high in fidelity. They offer realistic images from payload sensors and simulate various tasks in UAV operation [5] [14] [15] [16] [17][43] . A high fidelity synthetic task environment increases the likelihood that a controlled experiment would provide results that are relevant to the real world. However, a low fidelity synthetic task environment may suffice for some research [27] which is only interested in one task.
2. Participants in human-automation interaction studies in the UAV domain are not UAV operator practitioners but undergraduate and graduate students [14] [15] [16] [17] [27][43].
3. Operators are being placed in both single-task [5] [27] and multiple-task [14][15] [16] [17] [37][43] environments.
4. The synthetic task may involve control of one [14] [15] [16] [17] [43] or multiple [35][37] UAVs.
5. The range of synthetic tasks is broad and not consistent between studies at one institution, let alone between institutions.

6. Types of automation simulated include tracking, route planning, system monitoring, and target acquisition. The reliability of the automation was the independent variable in most of the studies. However, in no study is information about automation process or context presented in the interface. Moreover, while automation performance information is frequently provided, it is usually introduced either as part of the training or as feedback following a trial. These findings were very surprising to us. While we were not expecting to find research reports that referred explicitly to process, performance or context information in an interface, we did expect to find it in interfaces for UAV automation. Although it is possible that we have overlooked relevant literature, it appears that very little, if any, research has been reported on evaluations of interfaces to support operator interaction with UAV automation.

Experimentation

Cognitive artifacts were designed in this research to support operator's decision making process associated with automation on UAVs. The purpose of this experiment is to test the effect of those artifacts on operator's interaction with automation. In the experiment, the participants will be asked to complete multiple tasks in order to control one UAV in a target acquisition mission. Sensor fusion automation will be provided to help them detect and identify hostile targets. The output of the sensor automation contains uncertainty and its reliability is contingent on several context factors (e.g., weather, terrain and enemy camouflage). The cognitive artifacts convey the automation process and the context information to operators. We expect that these artifacts will aid participants in establishing appropriate levels of trust in, and reliance on, the automation. We further expect an overall increase of human-automation system performance in the target acquisition mission.

Introduction

The goal [45] to enable one operator to control multiple UAVs in the future implies that more and more tasks that are originally assigned to human operators will be reallocated to automation. However, automation on UAV systems is not always perfectly reliable, for example, the result from path plan automation [20] can be less than optimal, and the sensor fusion automation will be affected by noisy raw data.

Problematic Use of Automation

Human factors problems of imperfect automation have been noticed and studied for a long time. Parasuraman, et al. (1997) classified these problems into three categories: misuse, disuse and abuse of automation. Misuse occurs when operators excessively trust the automation and rely on it even when it fails. Studies revealed that highly reliable automation will lull operators into a state of complacency [2] [32] which undermines operators' ability to detect and respond to automation failures. Disuse happens when operators mistrust and fail to rely on capable automation. For example, Dzindolet, et al. (2003) found that people distrust even reliable automation after observing it make errors. Whereas the first two problems are related to operators, abuse of automation is a problem of system designers or managers, which occurs when they incorporate as much as automation into the system without considering the consequence on human operators, such as mental workload, manual skill degradation, loss of situation awareness and complacency [33]. Parasuraman, et al. (2000) developed the model of types and levels of automation to guide the implementation of automation in a particular system.

Trust in Automation

The problematic use of automation occurs when people fail to rely on the automation properly [24]. People's reliance on automation is affected by many factors, such as self confidence, trust in automation, perceived risk, and fatigue, amongst others [31]. Among all these factors, trust has been shown to be particularly important for understanding human reliance on automation. Therefore, engendering appropriate trust is seen as critical to supporting appropriate reliance on automation.

The appropriateness of trust depends on the user's knowledge about the automation aid: the performance history of the automation, the automation process, and the purpose of the automation [24]. In each of the UAV human-automation studies that we have reviewed, the purpose of automation has been provided to operators during training. In many studies, an indicator of automation performance (or expected performance) is provided as well, often in terms of a reliability level. Dzindolet, et al. (2003) suggested that it was not realistic to provide continuous feedback of automation performance to operators. Therefore in this experiment, only cumulative feedback of the automation performance will be provided to participants after each trial. With regard to process, Lee & See (2004) recommended showing the algorithms of the automation by revealing intermediate results.

For example, target detection automation first returns real-valued detection scores for each suspicious object and then thresholds these scores into binary categories to cue operators [38]. St. John, et al. [38] tried to help operators make better use of unreliable target detection automation by revealing the real-valued detection scores to operators. This changed the target detection automation from a target detector to an information tool for directing search. And the result indicated a general improvement in participants' detection performance.

One concern about revealing intermediate results to operators is the possible increase in workload due to the interpretation of those results [7].

Context, Automation, and Trust

Lee & See (2004) demonstrate that the appropriateness of trust can be divided into three dimensions: calibration, resolution, and specificity. Calibration is the correspondence between the trust level and the true quality of automation; resolution refers to how precisely trust differentiates levels of automation capability; specificity is the change of trust for different components in an automation system or over time. Calibration emphasizes the value -- the appropriate level of trust, while resolution and specificity highlight the discriminability. Sometimes the automation performance is not constant, and it can change over time or in different situations [7]. For example, the performance of UAV surveillance automation [20] varies according to the task characteristics, such as the number of targets, target distribution, target cost variability and spatial scale. In these cases, the correct calibration of trust is unachievable without high resolution and specificity, therefore resolution takes precedence over calibration [7].

One important reason for the variation of automation performance is that there are contextual factors in the environment that may not be explicitly considered in the automation algorithm but still affect the automation performance [24] [28]. Cohen, et al. [7] asserted that the "user must learn, or be trained, to recognize and act on uncertain quality about the automation and to understand how such uncertainty can change from situation to situation" (pp.1). Their dynamic

model of trust and reliance on automation [7] indicates that the context can influence the performance of the automation and therefore the calibration of trust often depends on how sensitive people are to the influence of context. The design implication common to both models is that automation designers must help users to relate context to the capability of the automation.

Several studies have attempted to explore the influence of revealing context to automation usage:

1. Dzindolet, et al. (2003) asked participants to indicate the presence or absence of a camouflaged soldier in still images with an imperfect automated decision aid. In their first study, they found that participants tend to distrust reliable aids after having observed it to make errors. In an attempt to mitigate this effect, participants in their second study were provided with an explanation as to why the automated aid might err: the decision aid may confuse a tree with soldier if the tree is in a human-like form. The results showed that the explanation increased participants' trust and reliance in decision aid. For those participants who were using highly reliable automation, the increase of trust and reliance was appropriate. However, for those using unreliable automation, the increase in trust was inappropriate.
2. Parasuraman, et al. (1993) examined people's reliance on system monitoring automation in a multi-task environment, in which automation with constant reliability lulled the participant into complacency. Bagheri (2004) replicated this paradigm but informed the participants the context-related nature of automation reliability. The result revealed that providing context information mitigated the complacency effect and improved participants' performance with constant and highly reliable automation.
3. Masalonis & Parasuraman (2003) tested participants' use of air traffic control decision aids. Two groups of participants were asked to detect potential conflicts between approaching aircraft pairs with the aid of an imperfect conflict detection algorithm. The reliability of the automation varied corresponding to two different scenarios, and this information was only given to one of the two groups through training. The result showed that both trust and reliance were affected by this context information. The trained group trusted automation in the two scenarios differentially and more appropriately. However, their overall performance didn't improve. This was because that the context information appeared to have a side effect of reducing participants' criteria to report a conflict, whereas the trained group tended to accept the automation judgment without question.

These studies provide initial evidence that providing operators with information related to the context affecting automation reliability does influence their trust and reliance on that automation. This knowledge appears to have helped participants to more effectively allocate attention to the automated task [2] and benefited the resolution and specificity of trust across situations. Thus, Lee and See's (2004) recommendation to "reveal the context and support the assessment and classification of the situations relative to the capability of automation" (pp. 75) appears to have empirical support.

However, contextual information may also have a down side, inducing some participants to rely on the automation even when trust is unwarranted [18] [28]. Therefore, the recommendation to reveal context information must be tempered by the recognition that this information may have an undesirable effect on an individual's decision criterion. Striking a balance between these concerns will require more extensive empirical evidence.

In all three of the studies mentioned above, context was revealed through training. Although this approach offers a relatively easy way to study the role of context in operator trust and reliance, there are several drawbacks to training. An alternative approach to communicating contextual factors is to include them in the operator interface.

We propose to design cognitive artifacts that convey the contextual-dependence of automation behavior. The interface approach may be preferable to the training approach for two reasons. First, training requires operators to remember the context information and recall it later during mission, and this occupies resource of working memory [42]. In stressful situations, working memory capacity is reduced (and the consequences of failure increase). An interface could places knowledge contextual impact in the world, thereby relieving the operator of a memory burden. Second, the nature of training determines that it can only provide information for anticipated situations. However, an interface can be designed in a way to provide useful information even in unanticipated situations, which characterize complex UAV missions [4].

Methods

The methods to be used in this experiment are drawn, in part, from those described by Wickens, et al. (2005). This is to take advantage of their prior experience in conducting human-automation interaction studies in a similar STE. Taking this approach will reduce risks in our experimental design without compromising our research objectives. As well, it will be advantageous to be able to compare results with those obtained by Wickens, et al. (2005)

Participants

Graduate students at University of Toronto Institute for Aerospace Studies (UTIAS) will be recruited to participate in this experiment. Graduate students were used successfully by Wickens, et al. (2005) and UTIAS students have participated in research studies in the past. These students are also the most convenient participants for this experiment because the STE will be located at UTIAS, which is removed from the main campus of the University of Toronto[7]. The participants will receive cash compensation and a bonus will be given to top performers. The compensation scheme follows that used by Wickens, et al. (2005) and has been found to be adequately motivating.

Synthetic Task Environment

Vega Prime 2.0 Simulator

Vega Prime is judged to be a leading candidate for a synthetic task environment for human factors UAV research[8]. Vega Prime is a commercial-off-the-shelf software application for the creation and deployment of real-time 3D simulation, training, and visualization applications. It is a high-fidelity environment, allowing for realistic, interactive aerial simulations. Its Graphical User Interface (GUI), Application Program Interface (API), and many extensible modules provide a high degree of flexibility and functionality. Vega Prime is used at several universities in North America, including the University of Toronto Institute for Aviation Studies (UTIAS).

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[7] …but close to DRDC-Toronto

[8] An early list of UAV simulators is included in Appendix A for information. The list is incomplete and does not reflect some of the simulators described above.

The information below was compiled from communication with UTIAS staff, Vega Prime vendors, university developers, the Vega Prime Programmer's Guide, a visit to the UTIAS facility, and content from the Vega Prime website.

Vega Prime Environment at UTIAS

UTIAS currently operates a Vega Prime environment consisting of three software components:

- Vega Prime is the scene graph manager that functions as the foundation of the program. It contains core C++ classes and functions. A screenshot of a sample scene window is shown in Figure 15.
- LynX Prime is a GUI tool that allows users to configure the scene graph in Vega Prime. It also contains an API to support programming interfaces in Vega Prime (generally for more experienced users). This is shown in Figure 16.
- GL Studio is a tool that aids creation of 2D or 3D graphical displays, including instrumentation models for simulation or training applications. GL Studio Plug-In allows the graphics to be integrated into Vega Prime such that the instrumentation can interact with the scene graph. For example, a dial graphic can be easily linked to the pitch of a plane without the need to write additional code. An example of the instrumentation generated is shown in Figure 17.

The following Vega Prime modules are not currently available at UTIAS but may be of value to UAV human-automation interaction experiments[9]:

- Vega Prime IR Scene provides real-time, physics-based generation of a scene at a variety of wavelengths from visible to infrared. It achieves this primarily using a physics-based approach to calculate the apparent radiance of objects with respect to the viewpoint of the user. A sample screenshot is shown in Figure 18.
- Vega Prime IR Sensor is an addition to IR Scene that adds realistic sensor effects, such as blur, saturation, jitter and various types of noise, to scenes generated using IR Scene. Post-processing done by IR Sensor helps to simulate sensor devices such as night-vision goggles or long-range infrared systems. A sample screenshot is shown in Figure 18
- Vega Prime Radar provides real-time, realistic 3D radar displays. A sample screenshot is shown in Figure 19.
- Vega Prime MAT creates atmospheric conditions.
- Vega Prime TMM (Texture Material Mapper) makes it possible to assign material classifications to textures in an IR database, which adds detail and realism to simulated sensor scenes. A sample database is included. This is being rolled into a module called "CTS Sensors."

[9] Pricing information for these modules is provided in Appendix B.

Figure 15: Vega Prime scene example

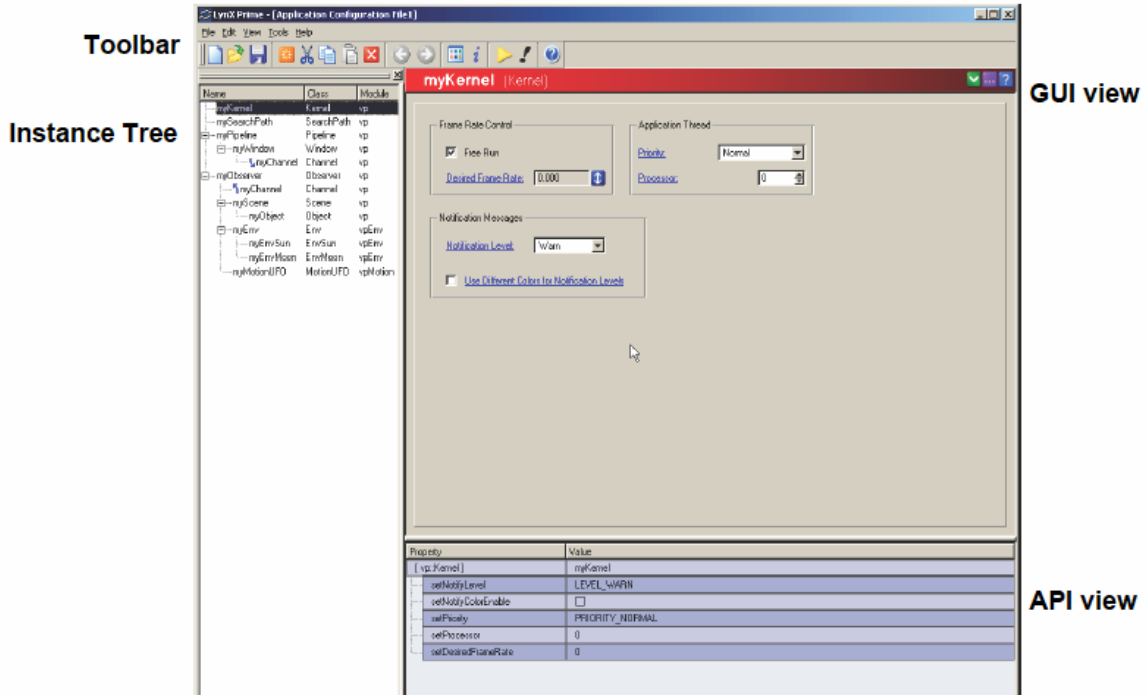

Figure 16: Screenshot of LynX Prime application

Figure 17: Instrumentation produced with GL Studio

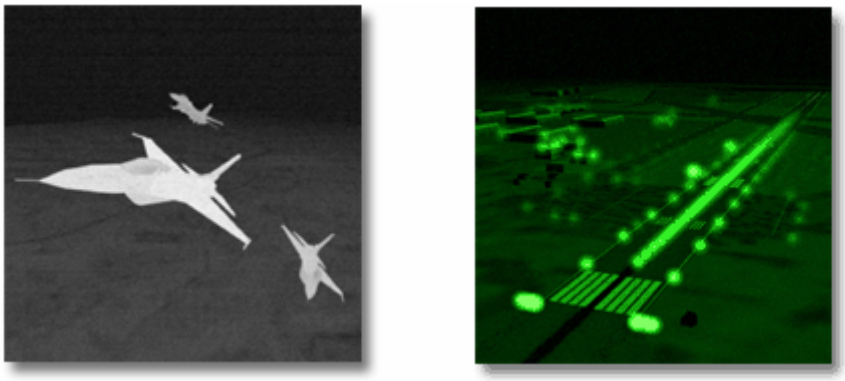

Figure 18: Screenshot of scene created using Vega Prime IR Scene (left) and Vega Prime IR Sensor (right)

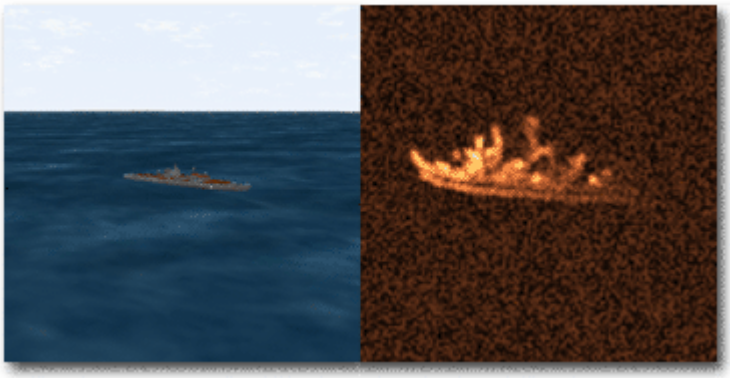

Figure 19: Screenshot of a Vega Prime scene (left) and corresponding radar return created using Vega Prime Radar (right)

UTIAS runs Vega Prime on a single Windows-based system with multiple monitors, including a touch screen. Vega Prime is available in two areas: one office space and one large laboratory that contains a motion-based flight simulator. Additional computers and monitors are present in both areas. Some rearrangement of the monitors would likely be required to create a functional testing environment, but there is sufficient room and flexibility in the hardware systems to do so.

Implementation Considerations

Vega Prime is a leading candidate for an STE for UAV human-automation interaction. It has the following advantages:

- The progress of the UAV can be simulated as if the aircraft were flying between waypoints and, if necessary, loitering around a fixed point.
- The sensor modules (i.e., optical camera, IR, radar, etc.) allow for simulation of the scene information obtained by UAV sensors. For example, we can simulate the image obtained from a camera mounted on the UAV panning across the scene. This functionality is already partially implemented in the UTIAS configuration.
- The display of the scene graph can be manipulated with the Vega Prime API to cue objects in the scene. This requires only a moderate amount of coding.
- Automation can be simulated with a "Wizard of Oz" technique—by scripting where, when, and how automation tasks are performed. This will allow for greater experimental control.
- Instrumentation can be easily linked to attributes in the scene through GL Studio.

A potential drawback of the Vega Prime system (at least in the UTIAS implementation) is that it does not have flight dynamics module or an image database for a UAV. Thus, they are currently unable to simulate the flight characteristics of a UAV and they cannot generate an image of a UAV. These drawbacks may not be serious[10]. Given that we do not intend to include the piloting task in our experiment, the flight dynamics will not come in to play. UTIAS has many aircraft models and it would be possible to select one that has a similar flight envelope to a UAV, yielding a sufficient level of fidelity for the experiment. The inability to view the UAV itself is also not a substantial problem because there is no need to see a UAV in the scene. Rather the tasks involve viewing the scene from an egocentric perspective.

Experimental Design

A 2x2 between-subjects repeated measures design will be employed in the experiment to test the effect of two types of information contained in the interface; 1) automation process information (present or absent), and 2) context information (present or absent). Thus, four experimental groups will be formed:

- Control Group: process information absent context information absent
- Treatment Group 1: process information present context information absent
- Treatment Group 2: process information absent context information present
- Treatment Group 3: process information present context information present

Experimental Tasks

Each participant will complete 10 mission trials (scenarios), each lasting approximately 10 minutes. In each trial, the UAV will fly a pre-determined path through a scene populated with targets. The primary task will be to identify the targets in the scene. Participants will be aided in

[10] We have not enquired with the UIUC about whether they are using UAV flight and image models. This might offer another way to circumvent this drawback.

this task by target identification automation comprised of two ATR systems and the DS sensor fusion automation described above (see Figure 20).

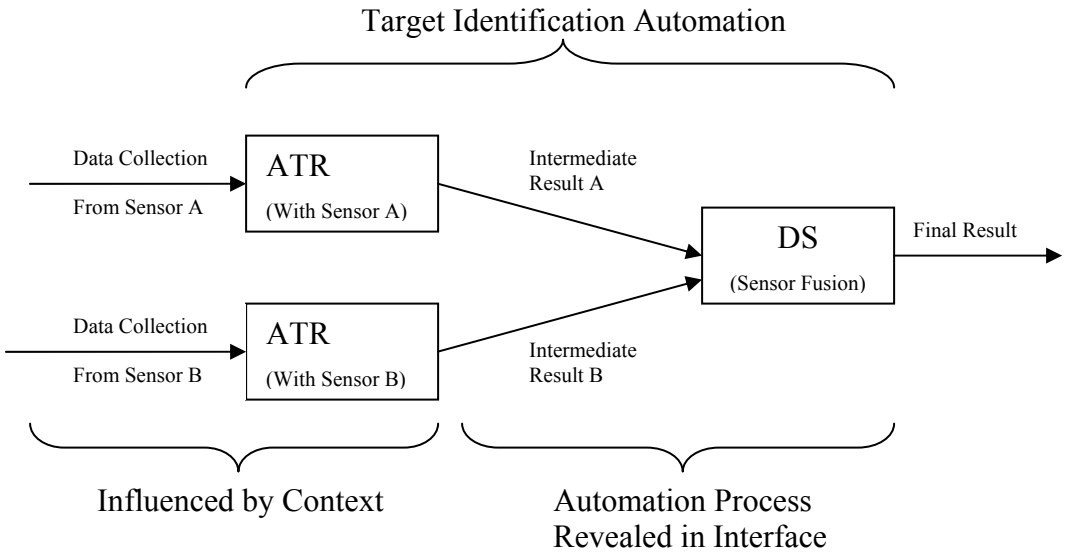

Figure 20. Sensor fusion automation flow chart

It may be necessary to introduce secondary tasks to increase the workload level[11]. An effort will be made to keep the difficulty level of each mission consistent. However, the order of presentation of the scenarios will be randomized to minimize order effects.

The location of hostile targets detected by the sensor fusion automation will be cued on the tactical situation map and the type of target will be indicated with text. In the three treatment conditions, additional information about the automation process and/or the context factors will be revealed through the interface as described above. The participant will respond by pressing a key or touchscreen location to designate the type of target. The participant will be free to use the automation process or context information (where provided) or the EO/IR camera (all groups) to acquire information about the automation conclusion or the visual scene, respectively. The training of the EO/IR camera will be automated in the simulation to control for spatial orientation skills. A key challenge lies in tuning the experimental scenario by balancing the payoff function and imposing time constraints (including delays in the camera pan and zoom) on task completion.

This automation will not make target detection errors. That is to say that all objects cued by the automation will be targets. However, the target identification could be wrong in either one of the ATR conclusions or in the DS sensor fusion conclusion. The automation reliability is computed as the rate of correct target type identification *by the DS sensor fusion automation*. The automation reliability will be constant within each trail, but will vary among trails with different context. In the 10 trails, the sequence of the automation reliability will be balanced across participants.

[11] For example, Wickens et al. [39] introduced a "target of opportunity" detection task and a system monitoring task to increase workload.

Participants will be given feedback about the performance of each type of automation (i.e., ATR and sensor fusion) at the completion of each trial. Note that this information is provided for all groups.

Procedure

A detailed experimental procedure will not be presented here. The procedure will generally consist of 4 phases: Informed consent, collection of demographic measures, experimental scenarios, and debriefing. Breaks will be given breaks between the phases and at regular intervals between the trials. The total experiment is expected to last 2.5-3 hours.

Measures and Instruments

The measures to be collected in the experiment are listing in Table 2 along with the instruments that will be used to collect them.

Table 2. Experimental measures and associated instruments.

Occurrence	Type of Measure	Data Collected	Instrument
Phase 2: One time	Demographic	General predisposition to trust	Four questions about trust in everyday objects [26].
		General self-confidence	Four questions about self-confidence in everyday tasks [26].
Phase 3: During each trial	Objective	Participant identification of each target	Simulation software
		Identification time for each target	Simulation software
		Verification strategy for each target[12]	Simulation software
		Performance of secondary tasks (if included)	Simulation software
Phase 3: After each trial	Subjective	Perceived workload	NASA Task Load Index (TLX)
		Self-confidence to fulfill target identification with automation	One direct question (10-point scale) developed by Lee & Moray (1992, 1994)
		Trust in the automation	Two options: One direct question (10-point scale) developed by Lee & Moray (1992, 1994). The 12-item trust scale designed by Jian, et al. (2000).

Note that the operator's self-confidence in her ability to complete tasks manually and her trust in automation have long been used as subjective measures in trust in automation research. However, Masalonis, et al. [28] suggested that as users learned how to accommodate the automation's failings and capitalize on its strong points, it will be more meaningful to questions an operator's self-confidence in his ability to complete the tasks with the automation. We include all three measures

[12] Whether or not, participants direct the video camera to the target location.

Hypotheses:

Main Effects

H1. Participants receiving automation ***process*** information will exhibit trust that is better calibrated, more resolved, and more specific as compared to participants not receiving this information.

H2. Participants receiving automation ***process*** information will perform better on the target identification task as compared to participants not receiving this information.

H3. Participants receiving automation ***context*** information will exhibit more better calibrated, more resolved, and more specific as compared to participants not receiving this information.

H4. Participants receiving automation ***context*** information will perform better on the target identification task as compared to participants not receiving this information.

Test and Evaluation Plan

The purpose of this section is to outline a test and evaluation plan for the experiment described above. Developing a synthetic task environment and experimental scenarios, implementing human-machine interfaces, and linking the various elements together are high risk tasks that will be prone to disruptions. Therefore, the tasks in this plan should be considered to be the minimum required to undertake the experiment. Similarly, the timeline provided is only an approximation and should be re-evaluated on a regular basis as the plan is executed.

Task	Milestone	Duration	Completion
Refine experimental plan[13]	DRDC sign-off on experimental plan	1 month	May 31st, 2006
Acquire radar and IR modules for VEGA Prime	Modules received at UTIAS	1 month	Jun. 30th, 2006
Develop synthetic task environment	Demonstration of functional capabilities of STE	2 months	Aug. 31st, 2006
Implement interface artifacts	Delivery of software code	1 month	Sep. 30th, 2006
Develop experimental scenarios	Demonstration of ten experimental scenarios meeting the requirements of the experimental plan.	1 month	Oct. 31st, 2006
Collect and prepare instruments and	Provide completed checklist of measures	1/2 month	Nov. 15th, 2006

[13] Refinement tasks will include: designing the appearance of the targeting cue, determining a compensation plan, setting the initial weights of the payoff function, setting the initial levels of automation reliability.

supporting documentation[14]	and associated instruments		
Conduct a usability study on the interface concepts		1/2 month	Nov. 30th, 2006
Run pilot study		1 month	Dec. 31st, 2006
Summative review of experimental design	Verbal agreement between DRDC and contractor that experiment is fully prepared	2 months	Feb. 30th, 2006
Recruit Participants	Produce list of participants and their assignment to groups	1 month	March. 31st, 2006
Data collection	All participants completed	1 month	April. 30th, 2006
Data recovery and treatment	Confirmation that all data have been recorded and extracted as required for analysis	1 month	May. 31st, 2006
Data Analysis	Produce complete statistical analyses of all measures	1 month	Jun. 30th, 2006
Reporting	Final report delivered to DRDC	2 months	August. 31st, 2006

Conclusions

This report has described a research plan for testing human-automation interfaces for UAV automation. The experiment is grounded in theory and practice of human factors scientists exploring the role of trust in automation as an important determinant of human automation reliance. A review of relevant literature in the domain suggests that the proposed study poses unique and important questions that, if answered, would comprise a significant contribution to the knowledge base supporting UAV automation design. Moreover, the results would be of broader interest to the human factors community as it addresses issues that cross domain boundaries. The risks inherent in the undertaking of a new research program should be further resolved and weighed against the expected returns.

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Appendix A: Review of UAV Simulators

Name	Description	Functionality	Flexibility	Fidelity	Popularity	Price	System Requirements
Multi-Attribute Task Battery	Allows users to perform multi-task workload and performance experiments.	Medium: Functions include system monitoring, tracking, a scheduling window, communications and resource management	Low: Written using Microsoft QuickBASIC 4.5	Low	High	Free: Available in lab now	Low: Available in lab now
Vega Prime V 2.0	A commercial off-the-shelf software, specifically designed for the creation and deployment of real-time 3D simulation, training, and visualization applications.	High: Users can manage details concerning numerous parameters associated with real-time, interactive visual simulation.	High : C++ development environment. GL Studio allows a user to easily insert interactive dials, gauges, and instrumentation. This flexibility has been **confirmed** by a programmer who served for UIUC research	High	High in academia	Vega Prime: $3999.50 Maintenance: $1439.10 Educational Program offers further discount	Medium: Windows workstation, 1.0 GHz or higher; 1+ GB RAM; 4+ GB hard drive; CD Rom drive; OpenGL 1.2 compliant graphics card; Windows XP Professional; Visual C++ 7.1
CAE UAV simulator	An integrated product that combines the Vehicle Control System from CDL Systems Ltd. with CAE simulation technology to form a vehicle operator station with a synthetic environment.	High: Fully-integrated command, control and information system designed for the control of UAVs	High: Fully integrates with CAE's STRIVE™ suite of products, allowing maximum expansion and flexibility in applications.	High	Unable to Judge: Has been sent to Defense Research and Development Canada (DRDC) as a research test bed	No detailed information. Note it is availabe in DRDC now.	Medium: Hardware: Additional video card for simultaneous display of video Operating Systems: Red Hat Linux 7.2 and 7.3; SUN Solaris 2.6, 2.7 (7), 2.8; HP-Unix 10.10, 10.20
Visual Computing and Engineering (VCE) UAV Simulator	Software developed for the US Navy. Provides a real-time 3D representation of the Predator UAV's daytime camera, which the user can control	Medium: Measure and track operator actions as they perform UAV payload operations and track ground objects.	High: Customization of the operating environment and mission scenario	High	Low: Used by Space and Naval Warfare Systems Command (SPAWAR) (US Navy)	Negotiating educational price	No detailed information now

Name	Description	Functionality	Flexibility	Fidelity	Popularity	Price	System Requirements
PCPlane	Flight simulator developed by NASA Langley Research Center	Medium: Contains Primary Flight Display (PFD), Navigation Display (ND) and auto-pilot/auto-throttle capabilities. Uses a Boeing 757 dynamics model.	Unable to judge: Can be integrated with Cockpit Displays of Traffic Info. (CDTI) and Multi-aircraft Control System (MACS)	Low	High: Used in many NASA projects/simulators	No detailed information now	No detailed information now
Cockpit Displays of Traffic Information (CDTI) / Advanced Cockpit Situation Display (CSD)	Display for air traffic that may be useful for us to integrate with other simulators	Medium: Provides information relevant to air traffic control, including position, ground speed and assigned track of multiple aircraft	Unable to judge: Can be integrated with other simulators, such as Multi-aircraft Control System (MACS)	Low	Medium: Used in some NASA projects/simulators	Free: download off website	Medium: Intel Pentium 4 processor NVIDIA chip based graphics card (GeForce 2 or higher) 256 Mb RAM 30Mb HD
Multi-aircraft Control System (MACS)	A research tool being developed by NASA to enhance realism and flexibility of air traffic simulations involving human monitoring.	Medium: Provides information relevant to air traffic control and management.	Medium: MACS uses Java and is conducive to rapid prototyping of user interfaces for various flight management and guidance functions.	Medium	Medium: Used by NASA and California State University	No detailed information now	No detailed information now
Aerospace Science (ASC) UAV Flight Simulator Station	A flight simulation used to study UAV operational concepts and to evaluate weapons integration risk.	No detailed information now	Unable to judge	Medium	Unable to Judge: Serves for defense client, cannot find specific client name.	No detailed information now	No detailed information now

Appendix B: Pricing for Vega Prime Modules

Table 3 lists the educational pricing for Vega Prime modules not yet available at UTIAS. Each additional monitor that a single Vega Prime system runs on requires a runtime license. UTIAS has the correct classifications and Export License to purchase these modules.

Vendor Contact:

Mary Beth Roselli
MultiGen-Paradigm
Maintenance and Educational Sales Rep.
Direct: (408) 878-0810
Fax: (408) 878-0895

550 S. Winchester Boulevard #500

San Jose, CA 95128

Table 3: Price list for Vega Prime modules.

Module Name	Base Cost	Maintenance	Runtime License (RTL)
Vega Prime IRScene	$14249.50	$3869.10	$1699.50
Vega Prime IRSensor	$6488.59	$1799.10	$799.50
Vega Prime Radar	$8749.50	$2474.10	$1099.50
Vega Prime Mat	$2849.50	$1025.10	N/A
Vega Prime TMM	$3874.50	$1394.10	N/A

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