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Automation for Human-Robotic Interaction: Modeling and Predicting Operator Performance

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Human-robotic interaction presents numerous challenges to designers and operators. One way to address these challenges is through task automation. However, appropriate application of automation, reducing workload while keeping the operator informed and in control, without causing skill degradation, is not generally understood. In this paper, we describe a human performance modeling and simulation approach to evaluating the effects of automation on operator and system performance. In this research, we identify and combine relevant factors that affect operator performance into operator-robotic system interaction models. The result of this project will be a partially-validated tool to help system designers evaluate potential automation strategies for their expected effects on operator and system performance.

This paper describes a unique research and development project to address human-automation interaction in robotic missions. In this project, we are developing the Function Allocation Simulation Tool (FAST) to help mission planners, automation designers and human performance researchers at NASA Johnson Space Center (JSC) evaluate human-automation interaction in space robotics missions. On the International Space Station (ISS), robotic equipment provides a primary means for performing repairs, and conducting docking, assembly, and maintenance tasks in the hostile environment of space. These robotic tasks offer multiple challenges. In particular, mismatches between the operator's viewpoint and the direction of movement of the robotic arm, and between the direction of control movement and corresponding arm movement adversely impact performance. Further, a limited number of cameras, few lighting options, and multiple potential collision surfaces add to the complexity of the task.

One potential solution for helping astronauts perform these missions is to automate the robotic tasks. Giving control to the automation could alleviate some of the operator's workload, but automation includes its own hazards. In particular, unreliable automation, or even highly-reliable automation that unexpectedly fails, can result in worse performance than continuous manual control (Wickens et al, 2010; Bainbridge, 1983; Parasuraman & Riley, 1997; Endsley & Kiris, 1995). As one example, if the operator expects that collision avoidance automation will prevent any impacts, s/he can become complacent, fail to diligently monitor the arm's position with respect to collision surfaces, lose situation awareness, and be surprised when the arm collides with a structure.

Other challenges with human-automation interaction include specifying how automation is to be implemented and the ways in which automation failures occur. Automation can be implemented so it takes over the "easy to automate" tasks. In these situations, it is typically the manual control tasks that get automated. This can reduce operator workload, but leave the operator removed from the loop. This can contribute to degraded operator situation awareness, and eventually cause the operator to lose their direct control proficiency.

Given the high-stakes missions in space, where collisions can damage expensive equipment, compromise mission completion, or potentially put astronauts' lives in jeopardy, it is imperative that human-automation allocations are carefully evaluated prior to implementation. Our approach to this work is to build human performance models of operators performing typical robotic missions, and have these models interact with an actual robotic simulation, to make predictions of human and system performance in different conditions. The tool we are developing, FAST, will allow planners, researchers, and designers to evaluate potential automation strategies, and identify their predicted effects on human and system performance, before implementing them. It will provide the opportunity to compare the effects of different types of automation by testing them (i.e., running simulations to gather data on predicted performance), evaluate the effects of sub-optimal reliability, and evaluate different types of automation failures.

The modeling and simulation (M&S) approach we describe in this paper has been used successfully in many applications (e.g., Allender, 2000; Foyle & Hooey, 2007). Modeling approaches offer the significant advantages of providing operator and system performance data without requiring human-in-the-loop research. The time and expense of obtaining institutional review board (IRB) approval for research with human subjects, planning and conducting studies, and the common problem of only being able to evaluate a few, limited scenarios is avoided. Models that represent situations being evaluated can be easily modified, allowing analysts to evaluate a wide variety of situations. Performance data can be gathered with a few computer key presses, rather than multiple experimental scenarios.

Human Automation Interaction in Space Robotic Missions

One of our first tasks in this work was to explore the domain of space robotics and identify the relevant human-automation interaction issues. We obtained a NASA JSC robotic simulation to include in the tool and attended a week-long Generic Robotics Training course offered at JSC. Based on the course, interviews with NASA robotics system instructors and a former astronaut, and findings from readings of the space human factors literature (e.g., Cizaire, 2007; Kanas & Manzey, 2008), we identified a set of potential automation concerns to include in the tool. The starting point for our model development was grounded in the stages-levels view of automation (Parasuraman, Sheridan & Wickens, 2000). This model defines stages of automation that correspond to different roles in an information processing / decision making / action framework. In this model, automation can support humans by: (1) gathering information and presenting it, (2) integrating information in such a way as to improve operator understanding, (3) supporting decision making by presenting options, and (4) implementing actions. Within each stage of automation, there are different levels, where the degree of automation increases. The following table shows how we characterize the robotic domain in terms of the stages-levels framework.

Table 1

Examples of Stages and Levels of Automation in Space Robotic Tasks

	Stage			
Level	***Information Acquisition***	***Information Analysis / Integration***	***Choosing / Deciding***	***Executing***
High	Automation highlights the camera view it infers is most valuable.	The automation diagnoses which control axis has excessive deflection	Automation assigns the best 3 views to the 3 viewports (but allows human to override)	Automatic control of XYZ trajectories, to points that are human designated
Inter-mediate	Highlights joints approaching singularities, potential collisions	Auto diagnoses collision state based on trajectory extrapolation	Automation recommends 3 camera views	Manual control of XYZ trajectories but automation control of joint angles
Low	Presents all raw data	None	Automation recommends a set of camera views to choose between	Manual control of joint angles

Following the task of identifying stages and levels, we identified a variety of specific types of automation, relevant to the robotic domain. These include trajectory control, camera control, lighting control, hazard alerting, and rate control. Within these different types of automation, there are different ways in which the automation can fail. Automation can simply fail to alert users, and lead them into an unsafe condition they were expecting to avoid. Automation can provide false alarms, alerting the operator to a hazard when none exists. Further, automation can recommend a suboptimal course of action; in the worst cases, this recommended course of action can be more risky than the one currently being performed by the operator. In the executing stage, automation can fail to implement an action correctly; it could choose and execute an incorrect trajectory for example.

Our current challenges include: determining the breadth of possible changes, identifying those most relevant to NASA, and focusing our research on a highly-relevant subset of those factors. Our main concern is to specify the automation conditions that can affect operator and system performance, and model these appropriately.

The goal of the project is to produce a Function Allocation Simulation Tool (FAST) that allows users at NASA JSC to evaluate predicted operator and system performance in robotic tasks under a variety of different automation situations. Thus, we have been actively identifying and specifying what types of automation are reasonable to consider, how these might fail, and what types of adaptive automation strategies might be included. These are all factors we will include in our software tool and in the operator models.

Tool Development

Software Development: FAST

FAST is a wrapper-based tool that includes a NASA JSC robotic simulation (The Basic Operational Robotic Instructional System, BORIS), a computational model of a human controller, known as MORRIS, and a user interface through which different scenarios can be created and evaluated. The MORRIS operator provides inputs to the BORIS simulation, and BORIS responses provide inputs to the operator model. The user interacts with the tool by creating and evaluating specific scenarios. Figure 1 shows a concept display for the data-entry screen. The user specifies what mission is being performed (e.g., moving to a destination, grappling an object, or performing an extra vehicular activity), what systems will be automated, how automation will be implemented, e.g., if trajectory control is performed manually by the operator using hand controllers or if the operator merely specifies the destination and the automation moves the robotic arm to that location and orientation. The FAST user also specifies if the automation is progressively adaptive, and if the automation is unreliable. Unreliable automation is further specified in terms of degree of reliability and type of failure. FAST users also specify aspects of the environment in which the task is performed, by placing obstructions (i.e., tables and no fly zones) in the area. Finally, users select the simulated operator's level of experience (i.e., novice, experienced, or expert). The tool then provides predictions of operator and system performance. FAST will allow users to evaluate and compare predicted performance across different automation conditions, to identify the best operating situation for the particular mission. Users have the flexibility to define the "best situation" according the parameters of most importance, e.g., minimal time to complete the task, most reliable performance, and/or lowest operator workload.

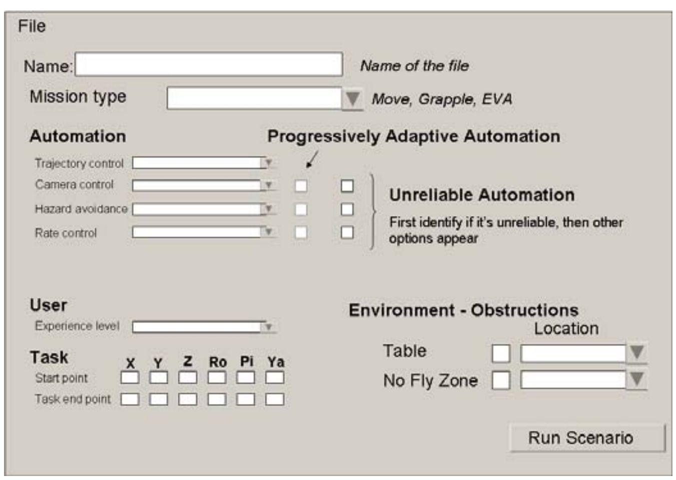

Figure 1. Concept of a FAST data entry screen, through which the user specifies the scenario.

Once users define a scenario, the tool sends parameters to both BORIS and MORRIS to configure the simulation and select the appropriate mission model, and set the human performance modeling parameters. By hitting Run the user initiates the simulation. The visualization of a run shows the following information (Figure 2 below): the BORIS screens of the robotic simulation (on the left) and the graphical user interface (on the right), the name of the scenario and time into the run, the operator performing the task and his SEEV-predicted viewcone (the area where the eyes are looking at any given time), and his/her predicted situation awareness and workload, and major events as identified in the interaction between the operator model and robotic simulation.

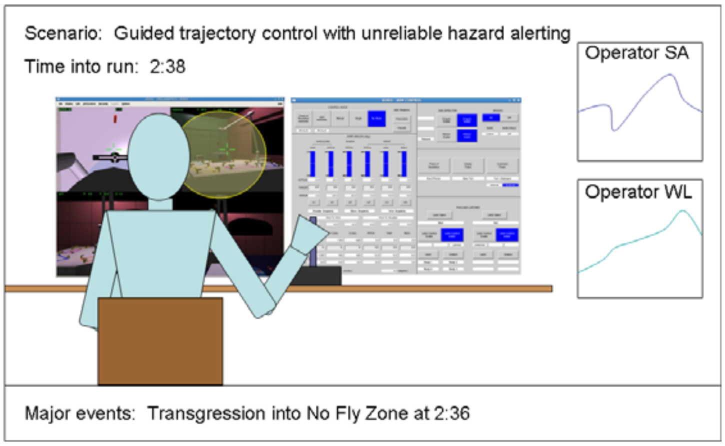

Figure 2. Sample display of the FAST scenario visualization capability, showing predicted operator performance.

BORIS Robotic Simulation

The Basic Operational Robotic Instructional System (BORIS) is a simulation environment consisting of a six-degree of freedom (DoF) generic robot arm in a simulated room with tables and payload latch-points. BORIS is the primary instructional aide in the General Robotics Training (GRT) program at NASA JSC, used for training general robotic arm control concepts and camera manipulations. BORIS provides a generic environment in which to encounter and practice many of the issues with robotic arm control. The BORIS training environment simulates a 15m x 30m x 15m room with a six DoF arm attached to one of two wall mounts. The room includes grids and distinguishing features on the walls. BORIS offers the capability to insert a large table, either for payload placement or as an obstacle, into the room (see Figure 3). Finally, BORIS has seven camera positions: a “window” view, four cameras mounted in the room corners, one at the end of the robot arm, and one mounted on the arm joint. The operator controls the arm through two hand controllers and receives feedback on arm position and certain features such as self-collisions and arm singularities (positions where automated arm movement fails) on a set of displays. In our simulation, a virtual operator will be controlling the arm, giving commands and receiving the update information.

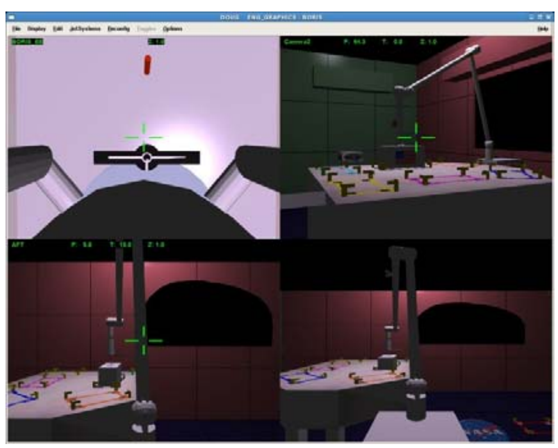

Figure 3. The BORIS training simulation, showing the robotic arm and operating environment

Operator Model Development

MORRIS: the computational model of the robotic operator

The goal of MORRIS was to create a software model of a robotics controller, working with BORIS, in a manner that generates the same sorts of errors, makes the same kinds of decisions, and experiences the same sorts of workload and situation awareness profiles (across a mission) as would the actual human controller. Initially, the model will be validated against human performance data from live operators controlling the equivalent systems. Then, to the extent that MORRIS is valid, it can be used to predict the consequences of different design, automation and mission changes that a mission planner would wish to predict. MORRIS attempts to incorporate the cognitive and physical aspects of the robotics task. Based on the inputs from our data collection efforts described previously, we refined and integrated three cognitive models, (Figure 4). The models represent decision making, spatial transformation (the Frame of Reference Transformation, FORT; Wickens, Keller, Small, 2010), and eye movements (Salience, Expectancy, Effort, and Value; the SEEV attention model; Wickens et al, 2009). These affect the critical operator behaviors of trajectory control, control mode selection, and camera view assignment, and contribute to predictions of workload and situation awareness.

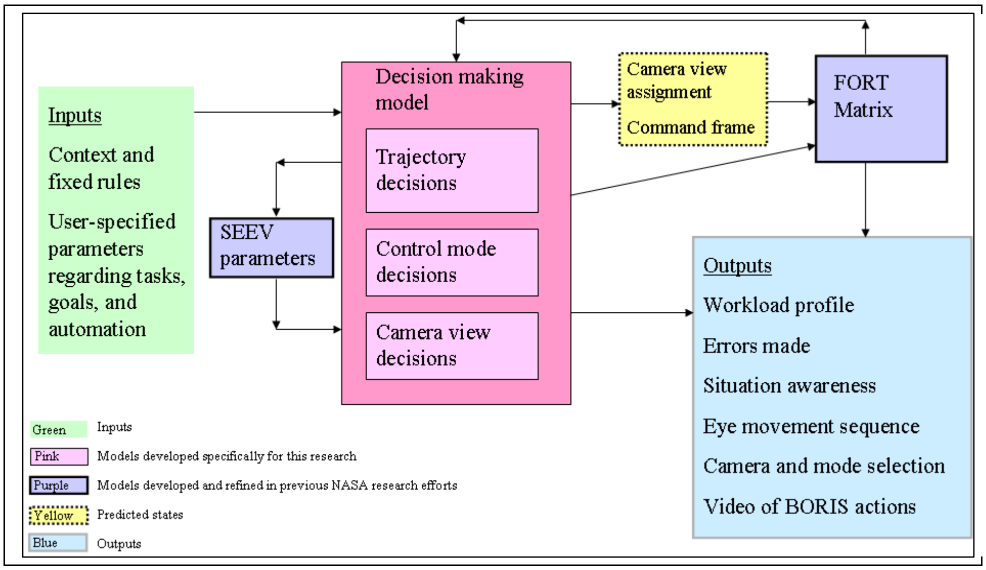

Figure 4. The simulated operator cognitive model, showing decision making, trajectory selection and attention.

The **decision model** makes three types of decisions: 1) ***trajectory decisions*** - how to move the robotic arm and whether to halt it in mid trajectory (e.g., if it should be approaching a hazard), 2) ***control mode decisions*** – which type of movement should be selected (e.g., rate of movement, arm-referenced or room-referenced movements), and 3*)* ***camera view decisions*** – which cameras should be selected for display in the three windows available to the operator. All of these decisions are based in part upon certain fixed if-then rules, where the "if" defines a context. For example if the end-effector is within 1.6 m of the target, then the slow, Vernier rate control mode should be selected. Importantly however, the decisions are also based on continuously varying **utility** of different choices, determined by continuous and changing variables as the arm moves through the workspace. Most of these variables are represented, cognitively, by the **frame of reference** with which the end-effectors is viewed in the cameras, and by which the control movement governs the arm movement. Thus a second model, the **(2) frame-of-reference transformation**, or FORT model provides critical inputs to all three classes of decisions.

The FORT model was developed for a broader class of spatial manipulations (Wickens, Keller & Small, 2010), and based on extensive empirical data from spatial cognitive operations (see Wickens, Vincow & Yeh, 2005). In the current project, we are modifying it to account for particular costs (cognitive and perceptual-motor challenges) imposed on the operator in the robotic environment, including line-of-sight ambiguity and control-display compatibility. FORT calculations are used to assess the quality of various camera views, and influence the modeled operator's decision to select a different camera view.

The **model of visual attention** across the workspace is **SEEV** (Wickens & McCarley, 2008; Steelman-Allen et al, 2009). The model is particularly important because it can predict attentional tunneling and **areas of neglect**, such as when an operator becomes so focused on a window guiding precise movement to a target, s/he fails to monitor another display that portrays the proximity of the arm's elbow to colliding with an object in the workspace. Essentially SEEV predicts the moment to moment scan between the three different camera windows and the master system monitor display (i.e., the GUI), based upon the **Salience** or each display, the **Effort** (proportional to distance) required to move the scan from one area to another, the **Expectancy** that information will change in an area and, most importantly the **Value** of each display to the robotics subtask in question. The FORT and SEEV models in FAST interact with one another, in that displays returning high FORT penalties are of low value, whereas those of low FORT penalties are of high value, and will be looked at much of the time.

Discussion

This paper describes the initial development of a model and simulation-based tool for predicting operator and system performance in robotic missions. The efforts described in this paper are being conducted to develop the FAST tool, to support researchers in evaluating human performance in potential robotic automation strategies, and help ensure that the design of new automation concepts does indeed support better operator and system performance.

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