Collaborative Human-Computer Decision Support for Planetary Surface Traversal

Jessica J. Marquez[*], M. L. Cummings[†], Nicholas Roy[‡], Maithilee Kunda[§], and Dava J. Newman[**]

Massachusetts Institute of Technology, Cambridge, MA, 0219

In support of the recent vision for humans to return to the Moon, we are studying decision support for planetary surface traversals. A key aspect of this investigation is the appropriate role allocations and balance between automation and human participation in the decision process. Some degree of automation is necessary during on-route replanning because there are many variables and models to consider within a short span of time. Yet, keeping the human in the decision-making loop is critical because astronauts will be able to more readily adapt to change and provide flexibility in problem solving tasks under unexpected circumstances. In this paper, we present a prototype path planner that allows human-automation interaction in the attempt to plan and optimize paths based on objective functions important to planetary traversals. One promising path planning visualization technique is based on the numerical potential field method (NPFM), which communicates to the user how the automation calculates least-costly paths. Our pilot experiment demonstrated that even with simple cost predictions for planned paths, all subjects planned a route within 25% of the optimal route. The results also suggest the NPFM visualization was particularly helpful for subjects tasked to create least-costly paths for a complex objective function.

Nomenclature

AS	=	Azimuth Score
EVA	=	extra-vehicular activities
LOA	=	levels of automation
LOEC	=	levels of equal cost
NPFM	=	numerical potential field method
PATH	=	Planetary Aid for Traversing Humans
SS	=	Sun Score

I. Introduction

On January 2004, a new set of human space exploration objectives were set forth: to return to the Moon, Mars and beyond[1]. Human presence on planetary surfaces will involve extra-vehicular activities (EVA) as part of the many surface operation activities, from construction work to scientific excursions. The types of Lunar and Martian EVA traversals could be diverse; for example, they could be conducted on foot or pressurized rovers, with or without robotic assistants, and may have multiple objectives to meet. From a cognitive decision-support perspective, a single traversing astronaut needs to manage navigation, physiologic- and mission-specific information, all in time-finite situations. Planning traversals on other planetary surfaces will be a time consuming task undertaken weeks and months before the mission, involving many scientists who will have to solve for a feasible path while keeping within the constraints and achieving mission goals. Managing all this information becomes increasingly difficult when the task changes to real-time replanning of a traversal, i.e., the astronaut must change and select a new path within a finite amount of time while not violating constraints. Astronauts will have many, and often, competing goals (for

---

[*] Ph.D. candidate, Aeronautics and Astronautics, 77 Massachusetts Ave, 37-219, and AIAA Member

[†] Assistant Professor, Aeronautics and Astronautics, 77 Massachusetts Ave, 33-305, and AIAA Senior Member

[‡] Assistant Professor, Aeronautics and Astronautics, 77 Massachusetts Ave, 33-315.

[§] Undergraduate candidate, Mathematics, 77 Massachusetts Ave.

[**] Professor, Aeronautics and Astronautics, 77 Massachusetts Ave, 33-307, and AIAA Member.

example, science objective versus safety constraint) for which they will have to find an acceptable satisficing solution. Real-time replanning computer aids will be required to support astronauts as they adapt to unfamiliar circumstances that accompany exploration in extreme environments.

In order to support replanning, we need to better understanding path planning under different types of computer assistance, concentrating on only one part of this larger problem: EVA carried out by humans on foot with their own life support system, e.g., spacesuit. In conjunction, we have assessed the Apollo missions to obtain "lessons learned" and develop tools that avoid repetitions of mistakes. In this paper, we discuss the need for human-computer collaboration for the task of path planning, the implementation of a potentially collaborative visualization into a prototype path planning tool, and preliminary results that test this visualization.

II. Background

A. Going Beyond Apollo

Pre-mission traversal planning for Apollo was a time-consuming task that occurred during the weeks and months prior to the mission. It involved the input of scientists, engineers, and astronauts to plan several traversals that would maximize scientific return and were feasible within the terrain and operational constraints[2]. For example, extensive preparation was undertaken for the field geology mission of Apollo 16. Each site and task was prioritized based on its relative importance to the overall scientific mission goal. Routes were established using pre-mission low-resolution photographic images and crude topographic maps, estimating traveling times and allocating finite times to the scientific tasks themselves. Yet, unexpected circumstances forced replanning: "The premission plan as finalized shortly before launch underwent modification during the mission as the science support team evaluated revised times available for traverses, problems that arose during the mission, and changing geologic concepts of the area being investigated."[2] During Apollo 16, the second EVA had problems with the lunar rover vehicle's navigation system as well as trafficability of the terrain.

The second EVA conducted by Apollo 14 astronauts Alan Shepard and Edgar Mitchell also incurred problems that required on-route replanning. Their goal was to *walk* to the rim of Cone Crater, which they failed to accomplish[3-5]. There were multiple reasons why the EVA goal destination was abandoned. First, the astronauts had poor situation awareness of their location; this was caused by the combination of inadequate surface contrast, sun position, and the monochromatic terrain. Consequently, they fell behind in the planned schedule. In addition, the path they actually walked resulted in high metabolic rates and increased heart rates. The only "tool" the astronauts had was a handheld map where the pre-planned traversal was drawn on aerial images of the Cone Crater area. Ground control kept time and reviewed their heart rates, but it was up to the crew's judgment to decide how to proceed with the traversal. The astronauts had to adapt to the reality of Moon exploration. They were in an unfamiliar environment, encumbered by bulky, life support systems, unaware of their deviations from the planned path, and attempting to resolve a problem where there were high costs (life threatening) for mistakes. In future planetary exploration, astronauts will need more than just a map; we should provide them with a decision support tool that will assist them during replanning of traversals.

Previous post-hoc analysis of Apollo traversals delineated some key parameters for assessing human traversals[3,6]. These parameters include path distance, metabolic cost, average slope, and visibility (line of sight and sun contrast). In order to maximize scientific objectives while keeping within safety requirements, future traversals should be planned to minimize particular objective functions, be it a single or a combination of the parameters previously listed. Each objective function must be modeled and incorporated into any planning or replanning tools. Our research focus is to understand how humans try to optimize these functions using computer assistance and different levels of automation.

B. Automation for Knowledge-Based Reasoning

Planning EVA is a task with a large problem space that includes surface models, physiological models, life support constraints, and other operational constraints. For on-route replanning, all these models and constraints must be integrated quickly as human space exploration is a high-risk and time-critical domain. Additionally, as astronauts spend more time away from Earth and with larger communication time delays (like on Mars), they will further rely on their own tools and less on Earth ground control. For these reasons, automated decision support tools will be integral for planning and replanning EVA on planetary surfaces, as this is a large problem space and too complex to be solved simply by hand.

While automation is a necessary component, three decades of research since Apollo demonstrated the potential effects of automation dependence on human task performance. When automation fails to work as expected, there is an increased chance for errors of omission and commission[7,8] and a decrease in automation trust[9]. Even when

automation functions correctly, there is the risk of inappropriate knowledge acquisition[10], inability to maintain mode awareness[11], lack of situation awareness[12,13], and skill degradation[14]. Many of these effects stem from over-reliance on the automation[15-17]. In order to keep both the automation and humans in the decision making process, these effects need to be mitigated.

One method for mitigating these effects is to properly balance the role of humans and automation, tailored to the specific task; suitable human-automation functional allocation is essential to this balance. Levels of automation (LOA) is a broad classification that describes different types of functional allocation within the decision process. There are several proposed lists of LOA[13,18-20]; the most referenced[19] is listed in Table 1. On one extreme, the human makes all the decisions and actions, and in another, the automation decides and acts; a middle ground between humans and automation constitutes collaboration. While open to interpretation, we propose collaboration falls generally under level 3. Although LOA provides a framework for discussing different types of functional allocations, the question still remains: what is the proper level of automation that will accomplish the selected task? Furthermore, how can we leverage collaborative strategies?

Table 1. Levels of Automation

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

The proper LOA is not obvious, and past replanning studies[21] within the aeronautics domain have argued for varied levels of automation (see Ref. 21 for review). Over-reliance and selection of sub-optimal solutions was shown for a replanning task that implemented LOA 4[15], yet some researchers were willing to overlook this under the additional constraint of time-pressure[22,23]. Moreover, some researchers do not advocate implementations of LOA 5 (and greater) for automated decision plans within high-risk domains[24]. For the task of traversal planning, the answer may lie in permitting users to collaborate with a path planning tool, making sure knowledge-based reasoning[25] is accommodated. Knowledge-based reasoning is the ability to make decisions under novel and uncertain situations that are not based on a predetermined set of rules, but rather adapting past experiences and judgment to solve a problem.

We propose that LOA 3 approximates what could be collaboration, though this definition falls short of all the factors that affect the level of collaboration between the human and automation. Collaboration can occur between two or more agents, a combination of people, computers, and/or robots. During collaboration, this group works together to achieve a shared goal[26], sharing intellectual efforts. Collaboration specifically between a human and a computer should exploit the strengths of both humans and automation in order to accomplish a task. Take, for example, the task astronauts face when on another planetary surface: adapting a pre-determined solution to an unexpected change within the large problem space. In these circumstances, it is important to keep the human "in-the-loop" during the decision process, as their inductive reasoning is essential to complement automation's potential inflexibility in handling unexpected scenarios.

One of the key aspects of our research has been to keep the human-in-the-loop through interactivity, and to help the user understand how the automation determines the best path. For our prototype path replanning computer aid, this was achieved by creating a visualization of the algorithm utilized in calculating a path. We in effect narrow the possible optimal paths for the user – mapping directly to LOA 3. It is important though to point out that the intent of the visualization is to both assist the user in making the correct paths and keep the user informed of how the automation is working. It is this type information communication that factors into collaboration.

III.   PATH: Planetary Aid for Traversing Humans

We have developed a prototype path planner that permits users to plan paths with minimal cost under different objective functions. Using this path planner, we are investigating the appropriate level of automation for the task and the cross effect with the type of objective function (Fig. 1). There are three developed versions of PATH (Planetary Aid for Traversing Humans), differentiated by *how* the optimal path is chosen by the user. The first version automatically creates a path, while another allows the user to determine waypoints to make a path. In the third version, a visualization narrows down the possible paths for the user, though humans must make waypoints for a path.
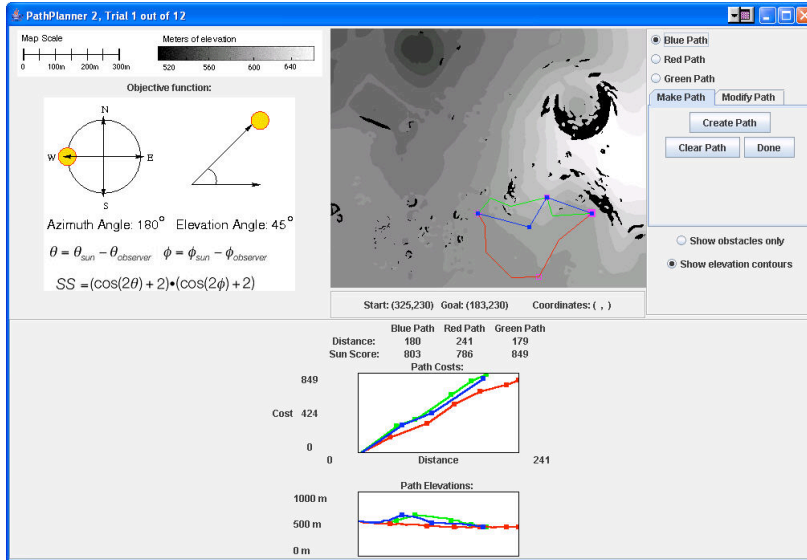

Figure 1. Screen capture of PATH. Elevation contour lines shown.

A. Common Functionality Across Versions of PATH

Currently, PATH utilizes lunar terrain elevation information from the explored Cone Crater area where Apollo 14 astronauts landed (Fig. 1). Obstacles (seen in black) are areas that are too steep for suited astronauts to climb. The sun's position is graphically (and numerically) shown on the left using the sun's azimuth and elevation angles. For this particular implementation of PATH, we are considering only environmental lighting conditions (though future additions will include variables such as metabolic cost). Below is the objective function and variables that determine the cost of a particular path. This function is pre-determined. A scale and a legend of the map are also included on the far left corner.

Users are able to make or modify up to three paths based on a given start and goal. The cost for each of the paths, based on the objective function, is automatically calculated and shown in the lower portion of the display. The associated costs are shown in a table and in a plot (the cost of each path segment is charted along the distance of the path). Also, an elevation profile shows the terrain elevation along the path.

Finally, regardless of how a path is created, be it by the user or by the automation, the user *always* has the ability to modify the path. With this functionality, the user can delete, add, and move waypoints along a selected path. The alterations can then be saved, and the display will update the cost changes. This is an important functionality as it permits the user to conduct a sensitivity analysis on their paths, tweaking the waypoints and assessing the cost penalties or benefits of the change.

B. Decision Support Visualization

There are currently three versions of PATH: manual, automated, and combination. In the manual version of PATH, the user must determine waypoints on the map to make the path. The first user-made waypoint is connected to the start with a straight line representing a straight-line path; each subsequent waypoint is connected with the previous waypoint in the same straight-line manner. When the user selects the goal as the last waypoint, the path is completed. Path segments that cross obstacles are not permitted and not accepted by the interface.

American Institute of Aeronautics and Astronautics

The automated version of PATH utilizes the numerical potential field method[27,28] (NPFM) in order to find the optimized path based on the given objective function. This method uses Dijkstra's algorithm[29] to search for paths in a grid decomposition of the space. The first step in NPFM is to discretize the state space. Each cell is labeled either as an obstacle, with an associated cost penalty, or a free space. The algorithm then determines the minimum cost from every cell to the goal based on the objective function. The penalty cost for that cell is also added to the minimum cost. If obstacles are given very high penalties, the minimum cost associated with that cell is always high. By doing this, one creates a "total cost" field for the space, where the goal has minimum total cost (usually zero) and obstacles are peaks of high total cost. In order to find the minimum total cost path (e.g., by avoiding obstacles), that is, the sequence of grid cells that incurs minimum cost, gradient descent on the total cost field is used. This version of PATH would correspond to level of automation 4 in that it would recommend a single best path.
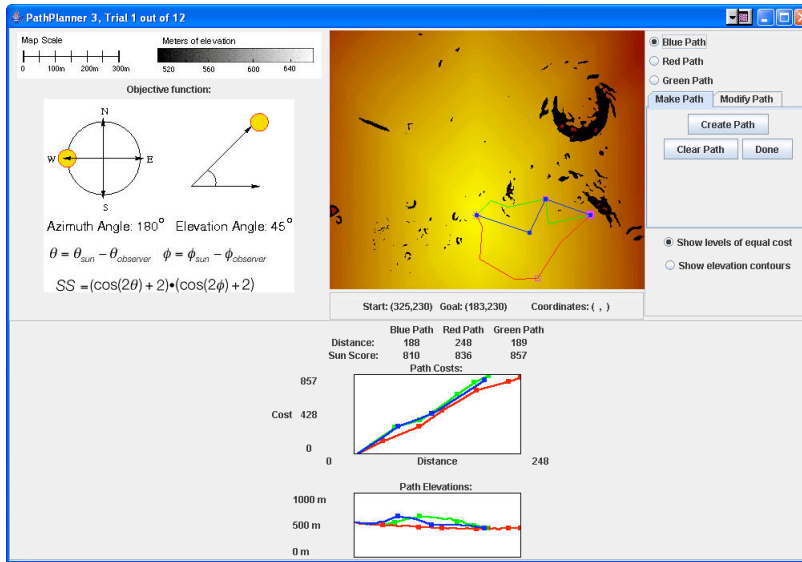

Figure 2. Screen capture of PATH with levels of equal cost shown.

The third PATH version combines the two previously described functionalities; the result is an interface that narrows down the possible paths for users through a visualization technique. Users have to make waypoints for paths but they do so with the visualization of the levels of equal cost (LOEC) generated by the NPFM (Fig. 2), helping the users see the high cost areas. To make the visualization, the "total cost" field is rendered using color, in a gradient fashion; each specific grid cell is colored relative to the total cost associated with each cell. The name of this display (LOEC) comes from the analogy it has with elevation contour lines. Between elevation contour lines, one knows that the relative height is the same for that area. Similarly, with LOEC, the same color indicates equal levels of cost. In this manner, the visualization reveals directions of minimum cost. This version of PATH falls under levels of automation 3. This visualization is very powerful not only because it narrows down the possible optimal paths, but also provides insight into the process of how the automation calculates minimum cost paths. This potentially can increase the user's situational awareness, allowing them to understand the underlying models and thus, create better paths.

IV.   Preliminary Results

A small pilot experiment was conducted that focused on testing the LOEC visualization for PATH. There were two groups of subjects: LOA 2 (no LOEC visualization) and LOA 3 (with LOEC). Subjects were asked to make an obstacle-free, least-costly path, based on the given objective function, start, goal, and sun position (environmental conditions). All subjects were asked to make paths based on one of two possible objective functions: Azimuth Score (AS) and Sun Score (SS). Finally, there were two possible orders in which the subjects saw the functions: either Sun Score first or Azimuth Score first. Thus, this was a 2 (LOA) x 2 (objective function) x 2 (order) experiment.

$$AS = \cos(2\theta) + 2$$
$$\theta = \theta_{sun} - \theta_{observer}$$
(1)

$$SS = (\cos(2\theta) + 2) \cdot (\cos(2\phi) + 2)$$
$$\theta = \theta_{sun} - \theta_{observer}; \phi = \phi_{sun} - \phi_{observer}$$
(2)

Azimuth and Sun Scores were the functions selected for this pilot experiment because only a single variable distinguishes them, thus we could assess the effect of adding one variable. A secondary objective of this experiment was to test if users could minimize cost functions that related sun position and direction of travel, as these are not common functions. Nonetheless, these functions are important for human space exploration because surface

visibility has demonstrated to be a key factor in the success and failure of planetary traversals. Azimuth Score (AS, Eq. (1)) relates the sun's azimuth angle and the person's azimuth angle (i.e., their direction of travel). The sun's azimuth angle was presented to the subject as a cardinal direction (north, south, east, west). The Sun Score (SS, Eq. (2)) takes into account the sun's elevation angle, linking it to the slope of the terrain (the observer's elevation angle). During the test trials, the sun's position, both azimuth and elevation angle, did not change.

There were twelve subjects, six in each LOA group, of which half saw AS first. Their average age was 25.8 ± 2.9 years, and most were graduate students. One subject was removed from the data set due to a failure to adhere to experiment rules. There were two dependent measurements in this pilot experiment: time to completion of task and cost of path.

The time to completion dependent variable was transformed (square root transformation) in order to have a normal distribution and equal variance across cells, a requirement to use ANOVA models for analysis. The ANOVA analysis yielded no significant difference between LOA 2 and 3 ($\alpha = 0.05$), meaning the LOEC visualization did not have an effect on how fast subjects were able to complete their task (Fig. 3). There was a significant difference between functions ($F_{(1,14)} = 4.407$, $p = 0.054$), so regardless of level of automation meaning subjects took longer when making paths based on Sun Score. This was expected, as SS is a more complex objective function compared to AS, having an extra variable to integrate in the path planning. However, there was a significant interaction between objective function and presentation order ($F_{(1,14)} = 4.454$, $p = 0.053$), which indicates a learning effect. Therefore, we cannot distinguish if the time differences were due to presentation order or the function itself.
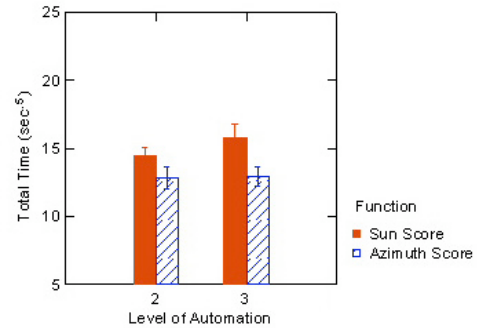

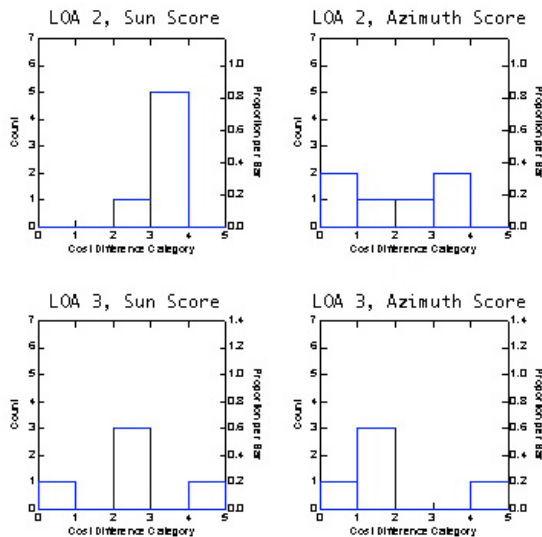**Figure 3. Average time (transformed) based on level of automation and objective function.**

Figure 4. Cost difference categories distributions by level of automation and objective function

For the second dependent variable, the subjects' path costs were compared to the minimum cost the automation calculated, resulting in a percent cost difference. Using this percentage also normalized comparisons between paths made to optimize AS versus SS. Results showed that all subjects, regardless of the level of aid, were able to generate paths within 25% of the optimal path. Since all cost differences were less than 25%, the errors were binned into five equally spaced categories (0 - 4.99%, 5 – 9.99%, etc.) and the differences in categorical distribution were analyzed. With respect to average path cost error, the distribution of cost difference categories was not significantly different between groups (LOA 2 vs. LOA 3), across all conditions (Fig. 4). In addition, using the Mann-Whitney U test, no difference was found within either objective function. However, the path cost errors were significantly ($p < 0.05$) smaller for paths made based on AS than those made based on SS. This makes sense, as subjects with the simpler function were able to achieve more near-optimal results.

However, these results should be regarded with caution, like the time dependent variable results. An analysis of the order in which subjects saw the functions revealed that some learning effect took place. Out of the four possible conditions, it appears that having LOEC visualization was very helpful when the first-seen function was the more difficult one, permitting subjects to make smaller errors than subjects without LOEC when minimizing the cost of a path. Thus, the combination of a challenging function and visualization was conducive to learning faster. Learning can be a significant confound for any experiment so another is currently underway that will rectify this problem.

V. Conclusion and Future Work

Understanding how path planning can be enhanced through collaborative elements is just one step in the process of improving computer decision support tools for human space exploration. Designing these first-generation systems for surface operations will involve the development of many models that are necessary to estimate energy consumption, equipment reliability, communication limitations, terrain characteristics, just to name a few. Because planetary exploration is knowledge-based task that cannot be easily automated, we need to facilitate the ease of use of computationally powerful computer aids by leveraging human-computer collaboration.

PATH was designed after having reviewed past Apollo EVA problems and assessed the information needs for future explorers. Our challenge was to devise a collaborative element that assist users in replanning traversals, whose cost is optimized based on a variety of objective functions. As a result, the levels of equal cost visualization was implemented. LOEC is helpful because it narrows down the possible optimal paths and provides insight into the process of how the automation would calculate least-costly paths. Based on the results of our pilot experiment, it appears that this visualization was to some extent successful, yet there is still room for improvement.

In the future, we will assess other aspects of PATH. Even though the pilot experiment showed that all path errors were less than 25%, subjects only attempted to manipulate one or two variables. More complex, and thus challenging, functions are planned for upcoming experiments, such as total traversal time, metabolic cost, and the combination of these with Sun Score. While observing subjects utilizing PATH, it was apparent that different strategies were implemented to complete the task. We plan to investigate these further and connect them to the appropriate visualization, so that we can better understand typical cognitive strategies. Finally, we would like to compare the effects of the visualization with the automated PATH version to explore the effects on situational awareness and selected strategies.

Acknowledgments

References

[1] NASA, "The Vision for Space Exploration", NASA Headquarters, Washington, D.C., 2004

[2] Muehlberger, W.R., "Apollo 16 Traverse Planning and Field Procedures," *Geological Survey Professional Paper 1048: Geology of the Apollo 16 Area, Central Lunar Highlands*, edited by G.E. Ulrich, C.A. Hodges and W.R. Muehlberger, US Government Printing Office, Washington, DC, 1981, pp. 10 - 20.

[3] Carr, C.E., Newman, D.J. and Hodges, K.V., "Geologic Traverse Planning for Planetary EVA," *2003 International Conference on Environmental Systems*, SAE International, 2003.

[4] Johnston, R.S. and Hull, W.E., "Chapter 2: Apollo Missions," *Biomedical Results of Apollo (NASA SP-368)*, edited by R.S. Johnston, L.F. Dietlein and C.A. Berry, NASA, Washington, DC, 1975, pp. 9 - 40.

[5] Waligora, J.M. and Horrigan, D.J., "Chapter 4: Metabolism and Heat Dissipation During Apollo EVA Periods," *Biomedical Results of Apollo (NASA SP-368)*, edited by R.S. Johnston, L.F. Dietlein and C.A. Berry, NASA, Washington, DC, 1975, pp. 115 - 128.

[6] Carr, C.E., "Distributed Architectures for Mars Surface Exploration," Master of Science Thesis, Aeronautics and Astronautics, Massachusetts Institute of Technology, Cambridge, MA, 2001.

[7] Mosier, K. and Skitka, L.J., "Human Decision Makers and Automated Decision Aids: Made for Each Other?" *Automation and Human Performance: Theory and Applications*, edited by R. Parasuraman and M. Mouloua, Erlbaum, Hillsdale, NJ, 1996, pp. 201 - 220.

[8] Skitka, L.J., Mosier, K. and Burdick, M.D., "Does Automation Bias Decision-Making?" *International Journal of Human-Computer Studies*, Vol. 51,1999, pp. 991 - 1006.

[9] Lee, J. and Moray, N., "Trust, Self-Confidence, and Operator's Adaptation to Automation," *International Journal of Human-Computer Studies*, Vol. 40,1994, pp. 153 - 184.

[10] Glover, S.M., Prawitt, D.F. and Spilker, B.C., "The Influence of Decision Aids on User Behavior: Implications for Knowledge Acquisition and Inappropriate Reliance," *Organizational Behavior and Human Decision Processes*, Vol. 72, No. 2, 1997, pp. 232 - 255.

[11] Sarter, N.B. and Woods, D.D., "Pilot Interaction with Cockpit Automation Ii: An Experimental Study of Pilots' Model and Awareness of the Flight Management System," *International Journal of Aviation Psychology*, Vol. 4,1994, pp. 1 - 28.

[12] Endsley, M.R., "Automation and Situation Awareness," *Automation and Human Performance: Theory and Applications*, edited by R. Parasuraman and M. Mouloua, Erlbaum, Hillsdale, NJ, 1996, pp. 163 - 181.

[13] Endsley, M.R. and Kaber, D.B., "Level of Automation Effects on Performance, Situation Awareness and Workload in a Dynamic Control Task," *Ergonomics*, Vol. 42, No. 3, 1999, pp. 462 - 492.

[14] Adelman, L., Cohen, M.S., Bresnick, T.A., Chinnis, J.O. and Laskey, K.B., "Real-Time Expert System Interfaces, Cognitive Processes, and Task Performance -- an Empirical Assessment," *Human Factors*, Vol. 35, No. 2, 1993, pp. 243 - 261.

[15] Layton, C., Smith, P.J. and McCoy, C.E., "Design of a Cooperative Problem-Solving System for En-Route Flight Planning -- an Empirical Evaluation," *Human Factors*, Vol. 36, No. 1, 1994, pp. 94 - 116.

[16] Parasuraman, R., Molloy, R.T. and Singh, I.L., "Performance Consequences of Automation-Induced "Complacency"," *International Journal of Aviation Psychology*, Vol. 3,1993, pp. 1 - 23.

[17] Parasuraman, R. and Riley, V.A., "Humans and Automation: Use, Misuse, Disuse, and Abuse.," *Human Factors*, Vol. 39,1997, pp. 230 - 253.

[18] Sheridan, T.B. and Verplank, W.L., "Human and Computer Control of Undersea Teleoperators," Man-Machine Systems Laboratory Report, MIT, Cambridge, MA, 1978.

[19] Parasuraman, R., Sheridan, T.B. and Wickens, C.D., "A Model for Types and Levels of Human Interaction with Automation," *IEEE Transactions on Systems, Man, and Cybernetics, Part A: Systems and Humans,* Vol. 30, 2000, pp. 286 - 297.

[20] Riley, V.A., "A General Model of Mixed-Initiative Human-Machine Systems," *Human Factors Society, Annual Meeting, 33rd,* HFES, 1989, pp. 124 - 128.

[21] Cummings, M.L., "Automation Bias in Intelligent Time Critical Decision Support Systems," *AIAA 3rd Intelligent Systems Conference*, AIAA, 2004.

[22] Chen, T.L. and Pritchett, A.R., "Development and Evaluation of a Cockpit Decision-Aid for Emergency Trajectory Generation," *Journal of Aircraft*, Vol. 38, No. 5, 2001, pp. 935 - 943.

[23] Johnson, K., Ren, L., Kuchar, J.K. and Oman, C.M., "Interaction of Automation and Time Pressure in a Route Replanning Task," *HCI-Aero*, AAAI, 2002.

[24] Sarter, N.B. and Schroeder, B., "Supporting Decision Making and Action Selection under Time Pressure and Uncertainty: The Case of in-Flight Icing," *Human Factors*, Vol. 43, No. 4, 2001, pp. 573 - 583.

[25] Rasmussen, J., "Skills, Rules, and Knowledge; Signals, Signs, and Symbols, and Other Distinctions in Human Performance Models," *IEEE Transactions on Systems, Man, and Cybernetics SMC-13,* Vol. 3, 1983, pp. 257 - 266.

[26] Terveen, L.G., "Overview of Human-Computer Collaboration," *Knowledge-Based Systems*, Vol. 8, No. 2-3, 1995, pp. 67 - 81.

[27] Barraquand, J., Langlois, B. and Latombe, J.C., "Numerical Potential Field Techniques for Robot Path Planning," *IEEE Transactions on Systems, Man, and Cybernetics,* Vol. 22, IEEE, 1992, pp. 224 - 241.

[28] Rimon, E. and Koditschek, D., "Exact Robot Navigation Using Artificial Potential Functions," *IEEE Transactions on Robotics and Automation*, Vol. 8, No. 5, 1992, pp. 501 - 518.

[29] Dijkstra, E.W., "A Note on Two Problems in Connexion with Graphs," *Numerische Mathematik*, Vol. 1,1959, pp. 269 - 271.