HUMAN-AUTOMATION COLLABORATION: DECISION SUPPORT FOR LUNAR AND PLANETARY EXPLORATION

by

JESSICA J. MÁRQUEZ

B.S.E Mechanical Engineering, Princeton University, 1999

S.M. Aeronautics and Astronautics, Massachusetts Institute of Technology, 2002

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Author: ____
Jessica J. Márquez, Dept. Aeronautics and Astronautics
February 1, 2007

Certified by: ____
Mary L. Cummings, Thesis Supervisor
Assistant Professor of Aeronautics and Astronautics
Director, Humans and Automation Laboratory

Certified by: ____
Dava J. Newman, Thesis Committee Chair
Professor of Aeronautics and Astronautics & Engineering Systems
Director, Technology and Policy Program

Certified by: ____
Charles M. Oman
Senior Research Engineer; Director, Man Vehicle Laboratory

Accepted by: ____
Jaime Peraire
Professor of Aeronautics and Astronautics
Chair, Committee on Graduate Students

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14. ABSTRACT

Balancing task allocation between humans and computers is crucial to the development of effective decision support systems. This thesis investigates the appropriate balance between humans and automation for geospatial path problem solving within the high-risk domain of human planetary surface exploration, where decisions are time critical and humans must adapt to uncertainty. In order to develop flexible and robust decision support systems for Lunar and planetary exploration, human-automation role allocations are examined to understand how humans conduct complex optimizations under different degrees of automated assistance. A work domain analysis of human planetary extravehicular activities (EVA) resulted in a framework for human-robotic planning, including key input variables, constraints, and outputs. Based on this analysis, a prototype path planning aid was developed. Under investigation was the use of partial automatic path generation and a visualization called levels of equal cost (LOEC, an aggregate cost map). Human-in-the-loop testing was employed to understand the effects of the automated assistance and different visualizations on path planning performance across multivariate cost functions. In two separate experiments, participants were tasked to make obstacle-free, least-costly paths based on given cost functions. Analysis of the experimental results indicated that knowledge-based reasoning is best supported when operators conduct manual sensitivity analysis, a strategy that was absent when path generation was allocated to automation. Leveraging computer-generated paths resulted in overall better path performance but also led to automation bias and decreased situation awareness. With respect to visualizations, participants using elevation contours had lower cost paths and short task times when automation was reliable. However, the LOEC visualization helped participants initially create least-costly paths for the most complex cost function. Furthermore, LOEC visualization appears to promote manual sensitivity analysis, which was beneficial in the degraded automation condition, where low cost and time was observed for participants with this visualization. Finally, two types of sensitivity analysis were observed, one that leveraged the available "what if" tools and the other that created whole paths. While there was no difference in path costs across the strategies, the increase use of the manual sensitivity analysis (i.e., path modifications) led to decrease path cost errors.

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Dedication

To the enduring stars that remind me constantly to keep dreaming.

In 1961, J.F.K. said: "...I believe that this nation should commit itself to achieving the goal, before this decade is out, of landing a man on the Moon and returning him safely to the Earth. *No single space project in this period will be more impressive to mankind, or more important in the long-range exploration of space*; and none will be so difficult or expensive to accomplish..." I am in awe that this statement still inspires me. I have spent so much time in this thesis work not just to get a degree, but because I truly hope that some piece, be it small or large, contributes to the endeavor of sending us (including me) back to the Moon and continuing onto Mars.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

1 INTRODUCTION

1.1 MOTIVATION

On May 25, 1961, President John F. Kennedy endeavored the United States to send a man to the Moon and return him safely to Earth, all within a decade (1961). Just three months shy of this deadline, Apollo 14 landed on the Moon, with Alan Shepard (the first American in space) and Edgar Mitchell. Among their tasks were to complete two extravehicular activities (EVA), or spacewalks, exploring the lunar area called Fra Mauro. In their second EVA, their destination was the edge of Cone Crater, an impact crater in the vast monochromatic lunar terrain. Along this traverse, the astronauts became uncertain of their location and began experiencing fatigue as they unexpectedly climbed steep terrain. These astronauts searched for Cone Crater, wearing bulky spacesuits, breathing hard, hundreds of thousands of kilometers away from Earth, and all they had to guide them was a paper map (Figure 1.1).

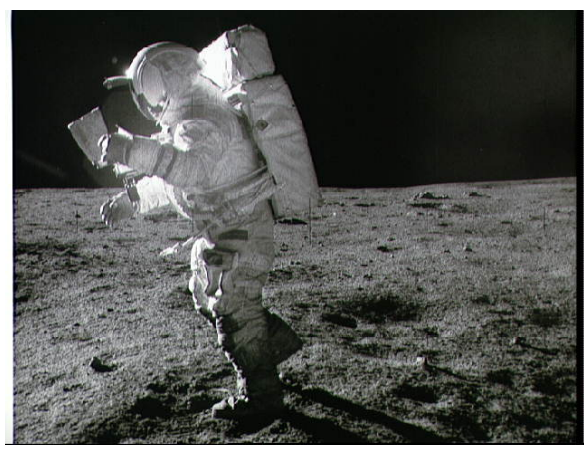

Figure 1.1 Apollo 14 astronaut with lunar map (NASA image: AS14-64-9089)

The feat of sending and returning humans to and from the Moon is extraordinary. A new national vision for human space exploration has been set forth as of January 2004, which includes returning to the Moon and going beyond to other planetary surfaces like Mars. Human presence on planetary surfaces will involve extra-vehicular activities (EVAs), either as part of field exploration, construction, or even recreation. In these futuristic settings, EVA traversals, be it on foot or on rovers, will become a routine, daily task. However, in light of the Apollo experience, there is still research and development that can be done to improve mission planning, productivity, and safety of EVAs, in particular, with the use of real-time decision support systems. Additionally, we can take advantage of thirty-five years of technological advancements. This thesis focuses on improving planetary EVAs through human and automation collaboration by investigating the real-time task of traversals planning and re-planning.

A successful, productive planetary exploration program must take advantage of the strengths of both humans and automation, be it computer aids or robotics. It is naïve to consider "robotic" and "human" missions as exclusively one or the other, when, in fact, all missions cannot be accomplished without the support of the other:

> "… in the space program it has been common to consider that a task must be done by either an astronaut or a "robot", that if a spacecraft is manned then astronauts must do almost everything, and that if a spacecraft is unmanned every task must be automated. In fact, on manned spacecraft many functions are automatic, and on unmanned spacecraft many functions are performed by human remote control from the ground." (pg. 205, Sheridan, 2000)

For instance, the Mars Exploration Rovers (MER) are two robotic agents that have successfully explored the surface of Mars for almost three years because of the enormous team of scientists and engineers operating them from the Earth. It is this assumption, that human-computer collaboration will be integral in future space exploration missions, which frames this thesis.

Planetary EVAs are complex, hazardous and safety-critical. EVA tasks currently conducted in microgravity already require automation, for example, for life support system control and remote manipulation of the robotic arm for positioning. From the technological perspective, planetary

EVAs require and depend on intricate life support systems for operations in extreme environments. Current pressurized space suits protect astronauts from the environment, for example, providing thermal regulation, but they limit mobility and senses, e.g., sound, vision, smell and touch. In addition, there is a limited supply of consumables, e.g., oxygen and battery power. Astronauts must also conduct their EVAs within prescribed safety constraints and operational requirements.

From a *cognitive* decision-support perspective, a 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 and engineers who recommend a feasible path while keeping within constraints and achieving scientific or mission goals. Managing all this information becomes increasingly difficult when the task changes to *real-time re-planning* of a traversal, i.e., the astronaut must change and select a new path in real-time within a finite amount of time while not violating constraints. Astronauts will have many, and often, competing goals (e.g., a science objective versus a safety constraint) for which they will have to find an acceptable compromised solution. Re-planning of an EVA is inevitable since "the unexpected" is inherent to exploration; maximizing mission success, productivity, and safety is linked to the astronauts' and mission controllers' ability to re-plan. Hence, a cognitive decision support system is would be essential in order to re-plan an EVA traversal in-situ.

Path planning and re-planning is not a task that is exclusive to EVA traversals; in fact, automated planners are becoming ubiquitous, and are integrated into daily activities such as driving. Geospatial problem solving also pertains to other "moving" objects, be it a soldier, an unmanned vehicle (air, ground, and underwater), a search and rescue robot, and manned aircraft. Any decision support system that involves these objects requires the human operator to conduct path planning. Thus, while the focus of this thesis is on human space exploration, the principles examined in this thesis, the human optimization process in a geospatial task, cut across all these mentioned domains.

1.2 PROBLEM STATEMENT

Traversal re-planning is a task that requires knowledge-based reasoning, where "faced with an environment for which no know-how or rules for control are available from previous encounters …

performance is goal-controlled and knowledge-based." (pg. 259, Rasmussen, 1983). Knowledge-based reasoning is necessary to support astronauts confronted with uncertain, novel situations. On the other hand, ruled-based reasoning is emphasized in the traditional methods of astronaut training, focusing on repeatedly practicing how to precisely accomplish a specific task in microgravity. Inevitably, there will be a paradigm shift in training – rule-based training will not be sufficient for future space exploration missions. Hence, any computer decision aids must support knowledge-based reasoning.

The central research question of this thesis addresses what is the appropriate way for decisions support systems to enable knowledge-based reasoning in geo-spatial path planning problems. In order to explore this problem, different human-automation role allocations are examined and tested in order to understand how humans conduct complex optimizations under different automated assistance. As a result, the aspects of human-computer collaboration that promote or detract from path planning performance are identified. In turn, this will help decision support system designers leverage human-automation collaboration to enable knowledge-based reasoning.

1.3 THESIS OUTLINE

The approach to exploring human-computer collaboration in a path planning task has followed general human-systems integration principles for the design and testing of decision support systems for planetary exploration. In order to develop a path planner, the operational environment needs to be first defined. This was accomplished through a work domain analysis of human planetary EVAs. Functional allocation between users and automation are determined, i.e., different automated assistance in support of users in decision processes. Human-in-the-loop testing is employed to understand the effects of the automated assistance on path planning performance. Hence, through experimentation, effective optimization strategies can be resolved. Finally, the requirements for decision support systems for real-time EVA planning and re-planning can be generated based on principled and comprehensive analysis. This thesis addresses each of these steps.

In Chapter 2, the benefits and drawbacks of automation are described and relevant past path planning studies are reviewed. This chapter identifies where this research fits in the overall field of cognitive systems engineering and research gap it addresses. Guiding hypotheses, which focus on the benefits of data integration, visualization, and role of sensitivity analysis, are also defined.

Chapter 3 provides a both a historical and pragmatic take on a work domain analysis for the prototype path planner. As the automation planner is intended for future lunar and Mars traversals, one cannot "go to the field" and study how planetary exploration in extreme environments is performed. Instead, a review of Apollo EVAs and the circumstances involved in planning and, more importantly, re-planning of lunar sorties completed. This overview is complemented with an observational study of excursions in a Mars-analog site in the Canadian Arctic. This chapter concludes by presenting a new Planetary EVA Framework that organizes all the parameters pertaining to planning and re-planning these traversals.

In Chapter 4, selected parameters and constraints from the Planetary EVA Framework were incorporated into a prototype path planner, aptly named PATH (Planetary Aid for Traversing Humans). This chapter describes in detail all the components of PATH, such as lunar digital elevation maps and the implemented cost functions. Most significantly, this chapter explains the importance of the developed collaborative visualization termed levels of equal cost (LOEC).

Chapters 5 and 6 summarize the two cornerstone experiments that were designed and implemented to understand how humans conduct complex optimization under various automation assistance and collaborative elements. Experimental hypotheses are delineated in each chapter, as well as independent and dependent variables. Results are presented and discussed alongside observed cognitive strategies; individual experimental conclusions are grouped by chapter.

The final Chapter 7 consists of a discussion of the conclusions of this thesis, a sensitivity analysis meta-analysis that aggregates results from both experiments, and design recommendations for path planning and re-planning decisions support aids, which includes a real-time EVA aids. Thesis contributions are listed and includes framework for human-robotic planetary EVA planning, path planning prototype, quantification of path planning performance across various conditions, identification of cognitive strategies, and design recommendations for planetary EVA decision support aids.

2 Background and Hypotheses: Balancing Humans and Automation Within Decision Support Systems

Balancing task allocation between humans and computers is crucial to the development of effective decision support systems. Within types of decision support systems, real-time path planning and re-planning is often a vital task which involve of both humans and computers. There are many domains that exemplify this, such as military and commercial pilots planning trajectories during flight or ground-based soldiers constantly revising their paths over the ground to accommodate dynamic changes in situations and resources. Similarly, unmanned air vehicle (UAV) operators also re-plan routes in response to emergent threats and targets. Robotic applications include tele-operation of rovers for situations like search and rescue missions and Mars exploration missions. In these cases, human geospatial problem solving is an integral part of the operator's interaction with the automated path planners.

Beyond complex decision support systems, path planning has become part of everyday life, with on-line automated planners like Mapquest[1] and Google Maps[2], hand-held GPS (global positioning systems), or in-car navigation systems. The alacrity in which path planning algorithms are being integrated into technology has created a sudden gap in our understanding of how people interact with automated planners and how different aspects of automation affect path planning performance. While methods for generating paths, or trajectories, for autonomous systems have been extensively

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[1] http://www.mapquest.com

[2] http://www.google.com/maps

studied within the computer science field in order to develop faster and more robust algorithms, little attention has been given to how humans optimize trajectories with automated assistance. In terms of human-automation interaction, few investigations have focused on how people optimize when conducting path planning in high-risk, time-critical domains that include a certain level of uncertainty.

The domain for this research is human space exploration, which embodies the definition of high-risk, time-critical, dynamic and uncertain environmental constraints. It is under these circumstances that astronauts will be expected to path plan (and re-plan) in order to optimize their extravehicular activities (EVA) on other planetary surfaces. With such a large problem space and resultant complex optimizations, humans will have to leverage automated path planners automation.

2.1 BENEFITS AND DRAWBACKS OF AUTOMATION

Automation is generally introduced as a way to reduce human workload, for example, by automating manufacturing processes. As computation ability has increased, automation has been used to help humans in tasks that were too cognitively intense (such as too many variables to control and/or excessive computations). For example, automation is essential in controlling the space shuttle. It is also used to help track and manage air traffic. However, the infusion of automation has changed people's responsibilities and work from active participation to monitoring and/or supervising. Thus, allocating the appropriate role to humans and automation, where the human is still in (or on) the loop of decision-making has been the focus of much research over the last fifty years.

The benefits of automation were succinctly summarized by Fitts in the 1950s (see Table 2.1). A computer's ability to be repetitive, fast, and precise is the reason why automation has become an integral part of all large, complex systems. These characteristics also make it ideal in the use of computer-generated path optimization, *when* the states of all variables are known and pre-determined. In juxtaposition, a human has unique abilities that even the most advanced automation systems still, more than fifty years later, do not have: improvisation, flexibility and, most importantly, inductive reasoning. This permits humans to adapt to unexpected circumstances, resulting in knowledge-based reasoning, the type of problem solving in which humans can make decisions under novel and uncertain situations (Rasmussen, 1983). Knowledge-based behavior (KBB) is goal-driven, and it assumes that the human has a mental representation and understanding of how variables in the problem space are interrelated. Based on this mental model, the person can execute deliberate actions to accomplish a goal, instead of simply following a set of predetermined rules (rule-based behavior).

Table 2.1 Fitts' list (1951) for human-computer role allocation

Humans are better at:	Computer are better at:
Perceiving patterns	Responding quickly to control tasks
Improvising and using flexible procedures	Repetitive and routine tasks
Recalling relevant facts at the appropriate time	Reasoning deductively
Reasoning inductively	Handling many complex tasks
Exercising judgment	Fast and accurate computations

Automation is governed by coded rules, resulting in an inflexibility to adapt under uncertainty, otherwise known as automation "brittleness" (Layton, Smith, & McCoy, 1994). The automation's "brittleness" in a highly uncertainty environment can be mitigated with human interaction (Figure 2.1). A similar argument exists in the system design world, where under changing or unknown system and environmental factors, a flexible engineering design is desirable (Saleh, Hastings, & Newman, 2003). Thus, for decision support systems, design flexibility is analogous to human interaction (Figure 2.2). This is important because the research domain of this thesis is space exploration, where "the unexpected" is an inherent quality of the domain. Any automated path planning aid must be flexible enough to support astronauts' knowledge-based reasoning while taking advantage of the strength of automation computation to produce adequate path solutions in high-risk and time-critical domains.

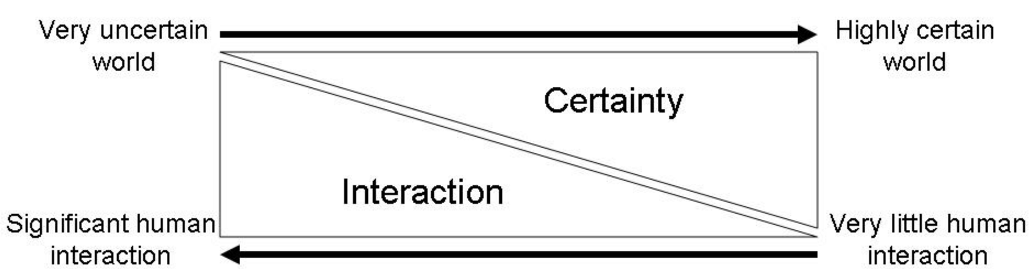

Figure 2.1 Human interaction with automation as a function of certainty (Cummings, 2006)

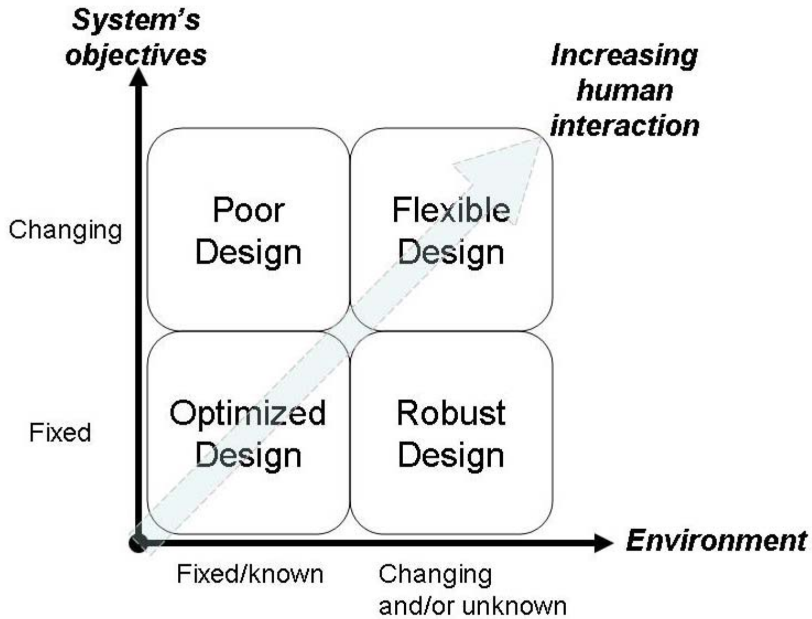

Figure 2.2 System's flexibility and robustness (Saleh et al., 2003), adapted to include human interaction

Automation "brittleness" can be caused by the models (e.g., of the environment or process) or the algorithm itself, as these could be either out-dated, incomplete or incorrect. Erroneous models are almost inevitable in domains in which any uncertainty exists. However, issues related to automation use go beyond the automation itself. For instance, humans could fail to understand the automation and the computer-generated solutions, resulting in users acquiring incorrect mental representations of the way the automation functions. This may be associated with the automated system's lack of transparency, where models are inaccessible. Even when automation works appropriately, researchers have found evidence for inappropriate knowledge acquisition (Glover, Prawitt, & Spilker, 1997) and skill degradation (Adelman, Cohen, Bresnick, Chinnis, & Laskey, 1993). When automation fails, users' trust in the computer aid decreases, which could lead to automation not being employed (de Vries, Midden, & Bouwhuis, 2003; Lee & Moray, 1994).

The use of automation may result in inability to maintain mode awareness (Sarter & Woods, 1994), which is similar to the degradation of situation awareness (SA) reported by others (Endsley, 1996;

Endsley & Kaber, 1999; Strauch, 1997). SA, as defined by Endsley, is (a) the perception of elements in the current environment, (b) the integration and comprehension of these elements, and (c) the projection of future status based on comprehension (Endsley, 1995). A loss of SA may be attributed to the human operators' lack of understanding of how and why a solution was generated by the automation. SA is crucial to the human ability to apply knowledge-based reasoning such that they can develop workaround strategies when automation fails or is unreliable.

Contributing to the human's lack of situation awareness may be another well-known problem, automation over-reliance (Layton et al., 1994; Parasuraman, Molloy, & Singh, 1993; Parasuraman & Riley, 1997). Over-reliance can be considered a symptom of automation bias (Cummings, 2004; Mosier, Skitka, Heers, & Burdick, 1998; Skitka, Mosier, & Burdick, 1999), which is the tendency by users (or decision makers) to disregard or not search for contradictory information about a computer-generated solution. As a result of automation bias, errors of commission and omission increase (Mosier & Skitka, 1996; Skitka et al., 1999). In errors of commission, the decision maker continues acting as the automation dictates even though there is evidence that the solution is erroneous. In errors of omission, the decision maker fails to intervene because the automation has not indicated errors.

While automation has many drawbacks, the answer is not necessarily to reduce the amount of automation. For example, within the domain of fault management, when the dynamics of a fault are fast, automation needs to be used to respond accordingly (Moray, Inagaki, & Itoh, 2000). Automation is indispensable for solving these time-critical faults, and the operator's role is still crucial. Automation is necessary within all decision support for complex systems, particularly when the tasks involve a large problem space under time pressure. Thus, essential to developing automated aids for planetary exploration is the balance between automation assistance and human interaction, while mitigating the issues previously listed (lack of automated solution transparency, loss of situation awareness, and propensity towards automation bias).

2.2 Path Planning Task and Automation Support

With respect to the geospatial problem solving, there have been few studies examining how cognitively humans optimize paths and only three that investigated the interaction between human path planning performance and automated assistance. This research is focused on the planning and optimization of paths, i.e., before execution and thus actual navigation with the path planner is beyond the scope of this thesis.

When no automated assistance is involved, a few studies have investigated path planning optimization. These studies focused on how people solve a traveling salesperson problem (TSP), which is finding the shortest path given a certain number of cities (nodes) with the constraint of having to visit each city once (Graham, Joshi, & Pizlo, 2000; MacGregor, Ormerod, & Chronicle, 2000; Pizlo & Li, 2003). TSP is considered to be a non-deterministic polynomial (NP) time complete problem, which means there is unlikely an algorithm that can solve the problem in a polynomial fashion[1]. Graham et al. (2000) found that subjects were good at finding close to optimal paths for when the distance between the cities were equivalent to Euclidean distance (E-TSP). Yet, when the distance was a multiple of the Euclidean distance (e.g., path segments were weighted), subjects did poorly. Their results with respect to shortest distance paths are not too surprising since the problem depended on the human's intrinsic ability to perceive relative size (Gibson, 1979), and hence, determining the shortest distance between points is a relatively easy task for humans. Nonetheless, this research confirms that when the path planning task goes beyond finding the shortest distance, it becomes a more difficult problem for the human.

In real world scenarios, the path planning task typically involves the integration of many more variables and most do not depend on the paths' visual size differentials. The cognitive process of path planning is summarized in Figure 2.3. First the human must acquire external information, such as environmental factors, variables and constraints, as each possible path plan depends on these numerous elements. This information then needs to be integrated with the set of goals that a path needs to meet, e.g., reaching a destination in the shortest time. The relationships between variables are defined through cost models. Cognitively, these models may be heuristics or, in the case of shortest path, they are perceptually driven (i.e., visual size differentials). Information, costs, and goals must be incorporated in order to create a path. The path planning process may be iterative, as

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[1] Currently, algorithms solve this problem in exponential times, as a function to the number of nodes.

the human could attempt several different paths that might satisfy the goals. It is up the path planner to asses each solution and determines if it is the best plan possible. Depending on the goals, a path plan might be an optimal path or it might simply meet some threshold (path cost satisficing). A path plan is only resolved once all these processes occur.

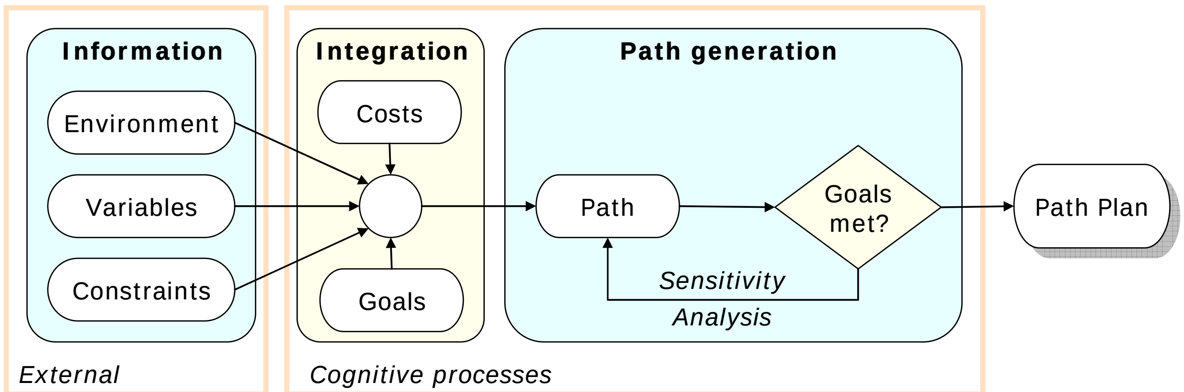

Figure 2.3 Cognitive model for path planning task

This path planning cognitive model is not unlike the simplified human information processing model presented in Parasuraman, Sheridan, and Wickens (2000), which includes sensory processing, perception/working memory, decision making and response selection. Sensory processing is akin to the acquisition of information, where all available input data enters for processing. The human path planner then must use his/her working memory to integrate inputs before suggesting a path solution. The path generation process is thus equivalent to the decision making stage. The loop within the path generation stage symbolizes that the information processing is not a strict serial sequence (also acknowledged by Parasuraman et al. 2000), but rather a process which includes attempting different path solutions and assessing these against the required goals. Finally, the response selection stage is the end state of the path planning cognitive model, where a path solution is determined.

The process of changing (or tweaking) a path solution (represented by the loop within the path generation phase) is the process of conducting sensitivity analysis on a possible path solution. For Saltelli (2000), sensitivity analysis "studies the relationship between information flowing in and out of [a] model." Essentially, sensitivity analysis is assessing the effect of changing input variables of a model or solution. Consequently, during path planning, it is the process of modifying a path, evaluating the change relative to the goal, and iterating until a satisfactory solution is achieved. Pannell (1997) lists decision making among the uses of sensitivity analysis, which includes testing the robustness of an optimal solution, investigating sub-optimal solutions, and identifying sensitive or important variables. Consequently, when the human path planner conducts sensitivity analysis, he/she is learning about how to optimize a path and this, in turn, may lead to a better understanding of how a solution (in this case, a path solution) is affected by changes in input variables (Saltelli et al., 2000). Thus, sensitivity analysis is an integral part of the path planning task.

For path planning, automation can be used in different parts of the cognitive process. The automation may integrate some of the information, like variables, environment and cost, for the human so that he/she does not need to calculate the total costs of the path solutions. Another possible example is that automation generates path solutions and the human selects the one that meets the goals. Wherever automation is leveraged, it will influence human path planning performance. A few studies (described subsequently) have investigated various methods of leveraging automation in the path planning task and the effects on human planning performance. These have focused on human performance within the domain of aviation decision making, specifically investigating path planning and re-planning of flight trajectories.

Layton et al. (1994) developed and tested a prototype en-route flight planner which required pilot participants' to re-plan an aircraft flight trajectory in order to adapt to a change in environmental conditions (see also Smith, McCoy, & Layton, 1997). Three versions of the planner were explored, each version differing in the amount of automation assistance provided. The lowest automation level possible allowed participants to "sketch" flight trajectories on the computer map, i.e., the human planner sketched paths and the computer filled in trajectory details such as arrival times. At the highest level, the computer interface, without prompting by the participant, provided a solution to the flight trajectory conflict. In the middle, the participant could ask the computer to provide a flight path solution based on selected constraints. The main result was that participants tended to over-rely on the computer-generated solutions, selecting sub-optimal paths. A possible reason was that participants did not explore the problem space as much when presented with a solution.

Chen and Pritchett (2001) evaluated a prototype computer aid for emergency aircraft trajectory generation (for divert conditions), simulating both plan and execution of new trajectories by pilots. The subjects' task was to create a new trajectory, under an emergency scenario, that minimized time to land and did not violate constraints, i.e., weather, airspace regulations, and aircraft limits. The authors tested three conditions: re-planning with no aid (only paper charts), with an aid, and an aid with pre-loaded plans. Performance was measured by time to land and workload. The worse performance was seen in the condition where there was an aid, but no pre-loaded plan. The best performance was achieved when pilots adopted the pre-loaded plans, though there was no significant difference with the test condition of no aid. The authors, however, favored the pre-loaded aid since in a few instances, pilots were unable to create and evaluate a satisfactory trajectory. This study also presented evidence for automation bias, as some pilots did not improve upon the sub-optimal, pre-loaded plan, as well as over-reliance that occurred when pilots accepted erroneous information presented by the automated aid.

In the third study, Johnson et al. (2002) investigated the effects of time pressure and automation on a route re-planning task. Participants were asked to make new paths that would first, satisfy mission constraints (avoid threat areas and arrive at targets within an acceptable time-to-target and sufficient fuel), and second, minimize route cost (time spent in hazard zones and deviations from time-to-targets). Six time pressures were imposed on the scenarios, ranging from 20 to 125 seconds. The automation would assist the participant in one of three possible ways: 1) suggest a route that met mission constraints, 2) suggest a route that met hazard avoidance rules, and 3) suggest a sub-optimal path that met both the constraints (time-to-target and fuel restrictions) and avoided hazard zones. A fourth condition, no path suggested, was also tested for comparison. Performance was measured by route cost and constraint violation. Based on their experiment, the authors concluded that full automation was most beneficial for the shortest time pressure (less than 30 seconds). The more time participants were given, performance differences decreased between automation assistances. The exception to this trend was around the 1 minute mark, when participants' performance decreased with more automation assistance. There was also evidence for complacency and automation bias, as noted by the decreased number of route modifications in the highest level of automation.

While humans have a natural capability of making shortest paths, as demonstrated by the TSP-related studies, path planning in real world scenarios encompass large problem spaces that may saturate the human's information processing capacity. Automation assistance can and should be leveraged to reduce the problem space, particularly under time pressure. The studies described above chose to insert automation in both the path planning processes of information integration and path generation (see Figure 2.3). Information was integrated through computer aids that would calculate path costs for users, such as arrival times. Path plans were generated for the humans, be it a complete or a partial solution. As a result, the human had to assess and judge if the path solution met the goals even though he/she had not partaken in generating the solution. Thus, these studies indicate that complete removal of human operator from the path creation process leads to complacency, over-reliance, and automation bias issues.

Even though sensitivity analysis is an integral part of path planning, none of these studies focused on how the automated interface may have affected this process. In fact, how humans conduct sensitivity analysis, the effect on human performance, and how best to support this process within decision support systems has received little research interest. Most of the literature related to sensitivity analysis centers on its importance for model development and validation (e.g., Lu & Mohanty, 2001; McCarthy, Burgman, & Ferson, 1995) and the mathematical methodology of conducting sensitivity analysis (e.g., Frey & Patil, 2002; Saltelli & Bolado, 1998). A few articles have advocated for sensitivity analysis tools for multi-attribute decision making aids (e.g., Jimenez, Rios-Insua, & Mateos, 2003; Triantaphyllou & Sanchez, 1997). However, no evaluation of the specific tools is mentioned, particularly in terms of human performance.

One series of studies has investigated interactive optimization, where the human and the automation are both involved in an optimization task (Anderson et al., 2000; Klau, Lesh, Marks, Mitzenmacher, & Schafer, 2002; Scott, Lesh, & Klau, 2002). Their description of interactive optimization is similar to sensitivity analysis because the researchers have tested a few methods that allow the human operator to change or modify solutions (in this case, path solutions for vehicle routing with time windows). These researchers also support the assertion that by allowing operators to guide or steer an automatic optimization process, operators will be more likely to understand a solution they helped create. Even though the experiments include less than a handful of participants, these studies have shown that interactive optimization is not detrimental in the optimization process and actually surpasses unguided search algorithms. These studies also point to different strategies implemented by the participants, but with as many strategies as number of subjects, trends were not assessed (Scott et al., 2002). Clearly, there is still much to be learned about how best to support human sensitivity analysis and the associated possible benefits.

This thesis begins to address the role sensitivity analysis has on human path planning performance. Furthermore, it focuses on introducing automation in the path planning process that will lead to sensitivity analysis, and hence collaboration between the human and the decision support aid. For instance, in the previously cited studies, either a path was automatically generated or it was left for the human operator to solve. This thesis investigates an intermediary state in the path generation stage of path planning, where the human leverages automation to create a path solution, allowing for sensitivity analysis and requiring the user to be actively involved in deciding a solution. This thesis also examines the impact of aggregate data visualizations for multivariate path planning problems.

2.2.1 LEVELS OF AUTOMATION

The previous section focused on allocating automation within particular stages of the path planning process. More generally, functional task allocation refers to the amount of automation used in decision support systems and the level of human involvement. For example, in Chen and Pritchett's computer aid (previously discussed), the automation was allocated the task of generating emergency aircraft trajectories while the pilot either accepted or modified these paths. Several frameworks have been proposed to describe these allocations, typically called levels of automation (LOA). These frameworks (subsequently discussed) help in the design of a path planning aid.

The most commonly cited levels of automation are Sheridan and Verplank's (1978) list which have evolved (Parasuraman et al., 2000) to a list of ten (Table 2.2). Sheridan's LOA range from one extreme, where the human makes all the decisions and actions, to another, where only the automation decides and acts. At the lower levels, the human takes a more active role in the decision making process, from finding a solution (or decision) to sorting through possible alternatives suggested by the computer. At level 5 (typically called management-by-exception), the automation begins to take an active role in decisions, and subsequently, the human is only required to accept or veto solutions presented to them. At the higher levels, the human is taken out of the decision-making loop altogether.

Table 2.2 Levels of automation (from Parasuraman et al., 2000)

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 previous path planning studies cited, the tested range of LOA tested was from 1 to 5. For example, Chen and Pritchett's (2001) emergency aid could be described as having LOA 4 since participants requested new trajectories, which the automation supplied. One version of Layton's et al. (1994) aid provided a trajectory without being prompted by the user, akin to LOA 5. It is important to note that Sarter and Schroeder (2001) suggest that automated decision support systems within high-risk domains should not implement LOA 5 as users may become vulnerable to automation biases.

While there are ten levels, this set of LOA fall short of describing many systems. If the lower levels (2 through 4) are applied to the topic of this research, human-computer collaboration within path planning, the role of the automation is essentially restricted to one or many paths generated. The biggest limitation of Sheridan's LOA is that there is no mention of how automation can assist in the analysis phase of the decision making process[1].

[1] In Parasuraman, Sheridan and Wickens (2000), the authors do acknowledge that a similar set of LOAs may be applied to information acquisition, information analysis, decision selection, and action implementation. However, no proposed list adapted to each decision process step yet exists.

Two other levels of automation frameworks are worth mentioning: Riley's and Endsley & Kaber's LOA. Riley (1989) describes a taxonomy of automation states (see Figure 2.4) where each state is a combination of the automation's role and level of information it can process (denoted as intelligence). Unfortunately, while proposing a greater resolution to Sheridan's LOA, it remains vague as to how automation is to fulfill these states (e.g., what must the automation do in order to be an assistant level of autonomy with personalized intelligence?). The general trend however is highlighted in Figure 2.4, where higher levels of intelligence and autonomy are desirable with increasing problem space complexity. Endsley and Kaber (1999) propose a ten-level taxonomy of LOA which depends on four generic functions (monitoring system status, generating options, selecting option, and implementing option) that could be allocated to either human, computer or shared. Each of the ten levels is some combination of function and role allocation (Figure 2.5). This taxonomy may be adequate to describe the type of decision support system implemented as a whole (as opposed to the level of automation), however, it is still vague as to what exactly is implied by shared (human/computer) allocation.

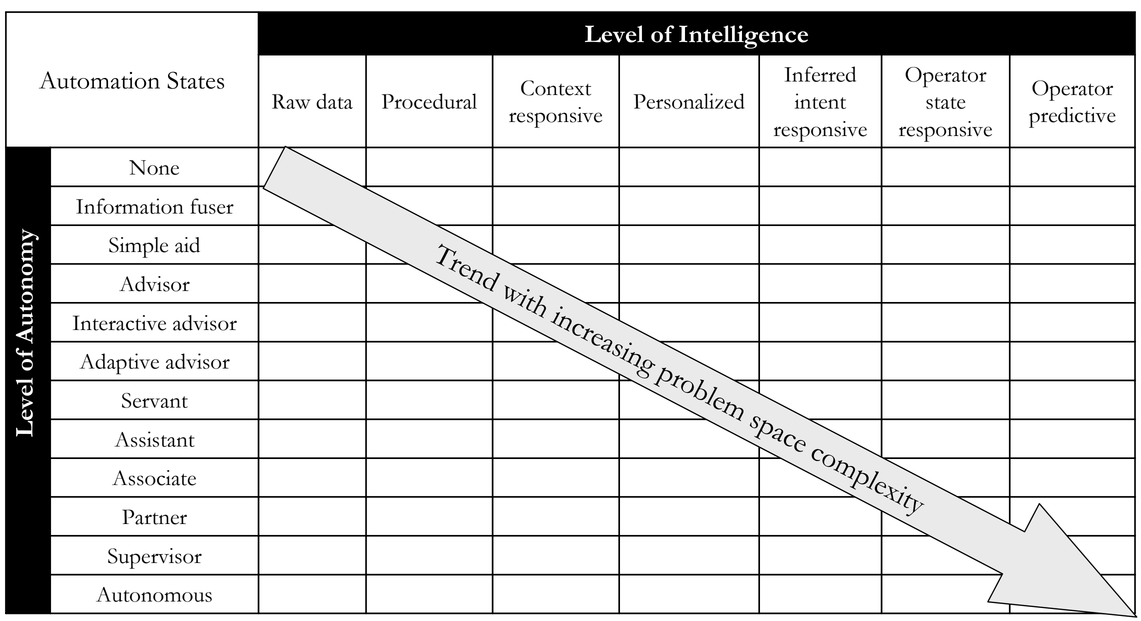

Figure 2.4 Riley's (1989) automation taxonomy, adapted to include trend with complexity

	Roles			
Level of Automation	Monitoring	Generating	Selecting	Implementing
1. Manual Control	Human	Human	Human	Human
2. Action support	Human/Computer	Human	Human	Human/Computer
3. Batch processing	Human/Computer	Human	Human	Computer
4. Shared control	Human/Computer	Human/Computer	Human	Human/Computer
5. Decision support	Human/Computer	Human/Computer	Human	Computer
6. Blended decision making	Human/Computer	Human/Computer	Human/Computer	Computer
7. Rigid system	Human/Computer	Computer	Human	Computer
8. Automated decision making	Human/Computer	Human/Computer	Computer	Computer
9. Supervisory control	Human/Computer	Computer	Computer	Computer
10. Full automation	Computer	Computer	Computer	Computer

Figure 2.5 Levels of automation by Endsley and Kaber (1999)

These LOA frameworks help in the design of an automated path planning tool. With increasingly complex problem space, more intelligence and autonomy is necessary, as implied by Riley's LOA. Riley's framework introduces the idea that a higher level of intelligence is more than presenting raw data. Furthermore, there is a specific level of autonomy for "information fuser". Thus, a path planning aid should leverage automation to integrate raw data for the human operator, particularly if the task is complex. The simplest method of integrating information for path planning is to calculate the paths' cost. Beyond that, visualizations may be used present integrated data. In terms of path generation, based on Sheridan's LOA, either the human operator or the automation may generate one or multiple possible path solutions. Present among the levels of automation by Endsley and Kaber is the option of a sharing the generation of solution functionality, i.e., both human and computer participate in creation of path. Thus, a path planning tool could be designed to accommodate path generation by the human operator, by the automation, or through a shared method.

2.3 HYPOTHESES

In general, previous studies suggest that for the task of path planning and re-planning, higher levels of automated assistance was beneficial for time pressured scenarios. Yet automation bias and over-reliance occurred in every instance, particularly when automated solutions were sub-optimal. While these studies focused on user performance with different LOAs, they did not attempt to quantify how well humans optimized under different task complexities or conducted sensitivity analyses. Moreover, there was no discussion of the impact of the visualizations used, which could significantly alter the results. These visualizations integrate information the human operators use to generate path solutions. A primary goal of this research is to examine not only the impact of increasing the amount of automation used in the path planning task on human performance, but also investigate the effects of visualizations in order to find an effective method of leveraging human-computer collaboration with respect to path planning optimization.

This thesis addresses two main guiding hypotheses, which result in analysis and investigation of different aspects of human-computer collaborative path planning under time-pressure, their impact on performance and optimization strategies, across increasingly complex problems. The more complex tasks include degraded automation conditions and cost functions that integrate numerous variables.

The first research hypothesis addressed is:

> *Hypothesis 1*: As the path planning becomes more complex, e.g., an increasing number of manipulated variables for the path planning task and degraded automation conditions, higher amounts of data integration through both computation and visualization will be beneficial for the human operator. These benefits include quickly creating near-optimal paths, maintaining awareness of important variables, and compensating for imperfect automation.

Data integration through computation includes leveraging automation to generate path segments and to calculate total costs. As other past path planning studies have already demonstrated problematic issues with using automation solely to generate path solutions (Chen & Pritchett, 2001; Johnson et al., 2002; Layton et al., 1994), this research will focus on investigating human-computer (shared) path creation. Furthermore, in this research, data integration can also be accomplished through a visualization that aggregates information (both variables and costs) based on the path planning algorithm used to search for least-costly paths. Thus, this visualization may simplify complex path planning problems for the human operator.

The second research hypothesis investigated is:

> *Hypothesis 2*: When a computer system that promotes sensitivity analysis is used for the task of planning (and hence, re-planning), human path planning performance will increase. Improvements include providing the human operator the ability to understand how to optimize paths, thus achieving near-optimal solutions.

No research to date has explored the role sensitivity analysis plays in the task of path planning in terms of human performance, even though it is an integral part of the human optimization process. Sensitivity analysis is the process of observing how much a solution changes as input variables are modified. Conducting sensitivity analysis is a more time-consuming optimization strategy, however, computational power can be leveraged to provide aids (usually called "what-if" tools) for the human operator that will assist in sensitivity analysis. This can be accomplished by making path modifications and corresponding evaluations easily available. If the human operator conducts sensitivity analysis, he/she will begin to acquire a better understanding of how to fundamentally optimize paths, which is particularly beneficial as the task becomes increasingly complex. As discussed before, task complexity may be a due to number of variables manipulated during optimization process or degraded automation conditions. For the latter, an increase in human path planning performance will be observed if the human operator successfully adapts path planning strategies and is able to quickly create near-optimal paths. Finally, as the role of sensitivity analysis will be concurrently investigated with different functional allocations for path generation and visualizations, potential cross-effects can be identified.

In order to investigate these guiding hypotheses, an automated path planner was developed and modeled as a planning computer aid for astronauts conducting extravehicular activities on the surface of the Moon. The prototype was built based on a work domain analysis of both Apollo historical evidence and observational study of excursions at a Mars-analog site. Two separate experiments were designed and tested, addressing the research questions presented in this chapter.

3 Work Domain Analysis: Characterizing Surface Operations

3.1 Extravehicular Activities on Planetary Surfaces

During the Apollo program, exploration was limited to a maximum 3 day stay, with two astronauts in bulky spacesuits, and the use of a lunar rover in later missions. Astronauts explored areas that were within a few kilometers of the lunar module. NASA is now considering lunar missions where up to four astronauts are traversing simultaneously on the surface of the Moon, taking advantage of pressurized or un-pressurized rovers (NASA, 2005). Future stays on the lunar surface will range from seven days to 180 days, with up to four sorties per week; Mars missions may last up to 600 days. As astronauts stay longer on other planetary surfaces, astronauts will be responsible for planning and re-planning of their own extravehicular activities (EVAs).

In order to design robust decision support aids for mission planning, the first step is to characterize surface operations of planetary exploration. This assessment is called a work domain analysis (WDA) because this investigation attempts to describe the structure of the domain, e.g., a planetary EVA, in terms of not just the tasks that are expected to be performed but also the constraints and impact of the environment. The goal of this WDA is to understand and identify the information requirement for a path planning decision support system. The work domain analysis presented in this chapter does not adhere to the rigid WDA definition (i.e., an abstraction hierarchical decomposition) presented in Rasmussen (1985) nor is it part of a formal cognitive work analysis (Vicente, 1999). The approach subscribed to is more general, focusing on identifying what information is required for planning an EVA by taking advantage of multiple methods, including field observations and review of documentation, elements that are more characteristic of a cognitive task analysis (Rasmussen, Pejtersen, & Goodstein, 1994; Schraagen, Chipman, & Shalin, 2000).

This work domain analysis is not a trivial task as future surface operations may consist of advanced technologies (e.g., robotic assistants), different objectives (e.g., acquiring in-situ materials), and a growing body of knowledge (e.g., new areas of scientific value). There are many likely combinations that depend on the infrastructure and mission goals. Hence, a myriad of complex extravehicular activities (EVA) architectures are possible. Instead of assuming one architecture, this chapter introduces a framework that captures the key parameters and constraints that define a single planetary EVA. Through the work domain analysis, planetary EVA variables, parameters that determine and affect path planning and re-planning, are identified and subsequently described. These variables are then categorized and organized into the Planetary EVA Framework. Thus, the framework is a summary of the work domain analysis, which was conducted by reviewing Apollo EVAs, performing an observational study of excursions in a Mars-analog site, and interviewing subject-matter experts, such as planetary scientists and aerospace engineers.

3.2 PAST EVAS: APOLLO PROGRAM

3.2.1 APOLLO EXTRAVEHICULAR ACTIVITIES

Every Apollo mission that landed on the Moon included at least one EVA. During the Apollo 11 and 12 missions, the EVAs focused more on engineering testing, while the EVAs performed during Apollo 14 – 17 missions were geared more towards exploration that addressed scientific hypotheses. Extensive preparation was undertaken in order to maximize scientific return, involving engineers, scientists, astronauts, and mission planners. Routes and estimated travel times were established using low-resolution photographic images and crude topographic maps. The team of scientists and mission planners also allocated finite times to the scientific tasks (Muehlberger, 1981). Each site and task was prioritized based on its relative importance to the overall scientific mission goal. Many activities or sites were dropped due to the lack of time, which is the underlying recurring theme among the lunar EVAs.

Some estimates were poor for the planned EVA tasks and thus, required additional time, affecting the rest of the schedule. During the first mission that astronauts walked on the lunar surface (Apollo 11), EVA preparation times were optimistic. Donning the spacesuit took longer than expected, delaying the start of the first EVA on the Moon (NASA, 1969). Delayed start times reduced the length of later EVAs, as was the case in Apollo 15 and 16. Since these missions landed on the Moon later than expected, sleep periods were rearranged so that astronauts would be rested when on the lunar surface (Jones, 1995), reducing the overall surface "work" time. Occasionally, deploying equipment, like the Lunar Rover Vehicle (LRV), was time-consuming, or worse, the equipment failed or worked inappropriately. For example, drilling on the Moon was difficult and took longer than expected for astronauts on Apollo 15 and 17. Any additional time beyond what was budgeted to accomplish tasks collectively resulted in changing the EVA.

The longest "walking" EVA[1] occurred during Apollo 14, where astronauts had to reach Cone Crater, a destination they never quite reached (Johnston & Hull, 1975; NASA, 1971; Waligora & Horrigan, 1975). With only a paper map in hand, encumbered by a bulky, life support system, astronauts had to traverse an unfamiliar environment, unaware of their deviations from the planned path. Astronauts had poor situation awareness of their location that resulted from inadequate surface contrast, lighting conditions, and the monochromatic terrain (Figure 3.1). In addition, astronauts traversed steep terrain that resulted in high metabolic rates and increased heart rates, requiring extra rest stops. Having fallen behind on their schedule and unable to accurately determine the edge of Cone Crater, their true destination site was abandoned and the astronauts had to settle for another site.

[1] The total average distance traversed was 1.5 km.

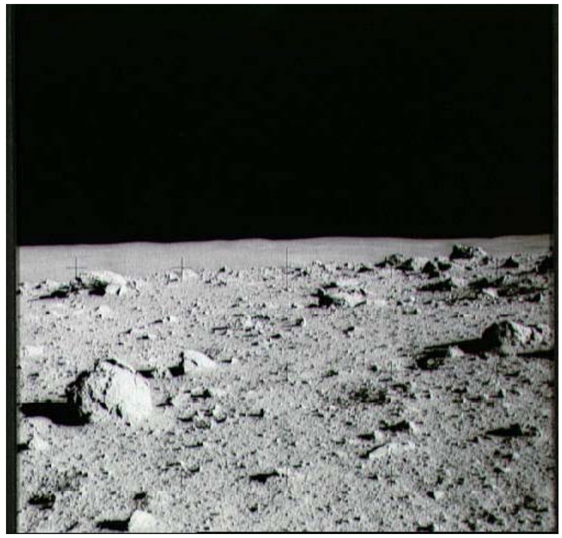

Figure 3.1 Edge of Cone Crater, Apollo 14 (NASA image, AS-14-64-9103)

The later Apollo missions included a rover (Lunar Roving Vehicle, LRV), which allowed astronauts to traverse longer distances, but additional concerns arose (Figure 3.2). Apollo 16 astronauts commented on driving slower because low sun angles made it difficult to estimate sizes (e.g., crater sizes) and distances (Jones, 1995). The LRV was yet another piece of equipment that experienced technical difficulties, such as a "down" navigation system (Apollo 16) and a lack of power steering (Apollo 15).

Figure 3.2 Lunar Roving Vehicle (LRV, NASA image, AS-17-147-22526)

The introduction of the rover to the EVAs imposed a strict safety rule: the "walk-back" requirement. If the LRV became inoperable, the contingency plan was for astronauts to walk back to the lunar module (LM). However, astronauts could potentially run out of oxygen before reaching the LM if it was too far. Therefore, the distance between the rover and the LM was limited by the astronaut's ability to walk back to the LM. Due to the "walk-back" requirement, the farthest sites had the most time pressure. This was the case during Apollo 17, when astronauts found "orange soil", which led to collecting an unplanned core sample (Jones, 1995). The crew had to quickly assess if they could accomplish the additional task given the time limitations. They chose to take the core sample, however, they used up all their time for that site and almost violated the "walk-back" restriction.

Finally, additional environmental constraints affected general performance, and thus, efficiency. During Apollo, the two significant environmental factors were lighting conditions (in conjunction with the lack of atmosphere) and dust. For example, Apollo 12 astronauts mentioned lighting conditions that made it difficult to properly assess rock samples (NASA, 1970). The pervasive lunar dust affected all equipment, resulting in deteriorated performance. Space suits were very dusty after only three uses, in most cases. Time spent cleaning equipment during an EVA added another, though small, delay.

3.2.2 IMPLICATIONS OF APOLLO EXPERIENCE

The successful completion of each planetary EVA during Apollo is a great feat. However, regardless of the many hours spent meticulously planning and practicing each sortie, every single EVA conducted in Apollo had to do some sort of re-planning in order to adjust to the unexpected. Over the course of one sortie, even small problems accumulate over time, requiring astronauts and mission controllers to adapt to the new time constraints. There are many incidents that resulted in time delays, the most prominent being underestimations of time required to complete tasks.

Table 3.1 summarizes the key variables, parameters that determine and affect planetary EVAs path planning and re-planning, identified through the review of Apollo excursions. These variables make up the specifics of the Planetary EVA Framework (discussed in section 3.5). Most importantly, the Apollo experience reveals that there is a complex relationship between these variables. For instance, the interaction between spacesuit, the terrain, and mobility was poorly understood, which consequently resulted in a very conservative "walk-back" requirement. There are still many unresolved issues left from the Apollo era, such as navigation and perception problems due to the Moon's environment. A better understanding of the relationship between variables will improve upon future safety and science-return of Lunar exploration.

Table 3.1 Planetary EVA variables based on Apollo EVAs

Variable Category	Variable Specifics
Astro-agent	Astronaut
Goals	Sites (number and locations), prioritization of sites and tasks, tasks at sites, costs associated with task (including time, energy, learning curve), additional unexpected tasks
Terrain	Characteristics (craters, large rocks, high slopes) related to obstacles
Exploration costs	Distance, time traversing, metabolic (or energy) expenditures, oxygen (and consumables) used, favorable sun positions
Transportation	Walking, driving; preparation time (spacesuit and rover); interaction between transportation and terrain & environment
Environment	Sun glare, illumination as affecting perception and navigation; dust
Infrastructure	Lunar lander, access to lunar rover
Consumables	Life support consumables specific to astro-agent (e.g., oxygen, CO_2 scrub, water, battery supply)
Operation rules	Safety margins (e.g., minimum remaining reserve oxygen), walk-back requirement, operationally required rest stops, maximum metabolic rate & heart rate
EVA components	Path (sites visited, path segments), schedule (time at site and traversing to waypoints), energy consumed along path segments

3.3 PRESENT EVAS: MER AND TERRESTRIAL ANALOGS

3.3.1 PLANETARY EXPLORATION BY MARS EXPLORATION ROVERS (MER)

Mars exploration is currently conducted on a daily basis by the two operational NASA Mars Exploration Rovers (MER). With respect to planning, a group of scientists and engineers meet every Martian day (sol) to decide on the sequence of commands for each rover (NASA-JPL, 2005a, 2005c). These generally relate to where to go, what activities to conduct (e.g., images to take), and where to position the rovers' arm (Biesiadecki, Leger, & Maimone, 2005). Decisions are made based on the previous sol's information, which includes not only imagery but also engineering information, such as the actual position and energy consumed by the rovers. If activities did not materialize as expected, engineers have to assess the reasons why and adapt to reflect the discrepancies. Mission planners typically allot one day (8 – 10 hours) to develop their plan.

The overall goals of the daily traverses are scientifically driven. This means that site selection and activities are identified by the science leaders. Exploration sites are determined based on imagery and spectroscopy data, and rely on planetary scientists' judgment for subsequent site selection. The sites that each of the rovers have investigated were not pre-determined on Earth, except the landing location. All other sites were selected in-situ, and were resolved based on previous findings, as is the nature of exploration (Zuber, 2006).

In order to interact with the rovers, scientists and engineers (on the ground) use the Scientific Activity Planner (SAP) (Norris, Powell, Fox, Rabe, & Shu, 2005; Norris, Powell, Vona, Backes, & Wick, 2005). SAP is the primary science operations tool that provides planning capabilities for the MER. Scientists and engineers have access to imagery that includes panoramas, camera views, and hyperspectral visualizations. Processed information includes "reachability" maps (relating to where the instruments can reach), slope, and solar energy maps (Leger, Deen, & Bonitz, 2005). After locations of interest are marked, a simulation predicts rover details like the power consumed, the data volume, time required, and final position (Norris, Powell, Fox et al., 2005).

Key to the rovers' ability to conduct exploration is their navigation ability. The MERs' tele-operators define waypoints and end goal states. The rover then can assess and determine the actual path, avoiding obstacles. However, defining an 100-meters drive sequence may take an operator between 2 to 4 hours (Biesiadecki et al., 2005). This is due to the manual terrain analysis that is incorporated in the process. There are many terrain properties that are important: slope, elevation, rock size & position, terrain quality (e.g., sand, firmness), and homogeneity of terrain. Many of these influence how the rovers traverse including speed, slippage, and power required. If the rover encounters a navigation problem, the operator intervenes. For example, one of the rovers inadvertently buried itself into a sand dune (Biesiadecki et al., 2005; NASA-JPL, 2005b). The rover followed its driving commands until it realized that it was no longer advancing. At this point, the rover went into a safe mode ("alive" though waiting for new instructions), alerting the engineers of the problem. After weeks of terrestrial testing drive configurations and strategies, engineers were able to command the rover out to safety. Such an incident highlights the importance of operators, particularly in dealing with terrain uncertainty.

Assessment of on-going MER planetary EVAs identified additional variables, beyond the Apollo experience, that need to be taken into account by a comprehensive path planner (Table 3.2). Future human exploration will likely be similar to that conducted by MER, where sites of interest are based on recent discoveries, requiring an up-to-date database of imagery, spectral data, and terrain properties. Most importantly, the experience with MER highlights the value of operator and rover interaction. In this case, it is the human that intervenes when the robotic agent is affected by unexpected events, such as the Martian terrain uncertainty. In turn, future robotics agents could also prevent humans from making mistakes.

Table 3.2 Planetary EVA variables based on MER exploration

Variable Category	Variable Specifics
Astro-agent	Robotic agent (tele-operated rover); capabilities of agent (instrument- or task-related)
Goals	Determined by on-going exploration
Terrain	Rock density, ground bearing strength, homogeneity, slope, elevation, spectral data
Transportation	Minimum ground bearing strength, maximum traversable slope, maximum speed (function of terrain), power requirements, admissible slippage
Environment	Wind; seasonal solar supply
Consumables	Power supply/source, life cycles of robotic agents' components

3.3.2 PLANETARY EXPLORATION STUDIES USING TERRESTRIAL ANALOGS

Two studies, Carr (2001) and Clancey (2001), have used terrestrial analogs to investigate human planetary exploration, specifically focusing on EVA. While Carr emphasized trades between transportation and communication ability for lunar exploration, Clancey focused on information flow between explorers when planning.

Carr (2001) examined the effects of distributed architectures for Mars surface exploration. There are two major components of this research that pertain to planetary EVAs: a month-long field geological mapping project that was placed into the context of planetary surface exploration, and an in-depth analysis of Apollo EVA traverse to Cone Crater. From his field experience, he emphasized the importance of the providing the explorer with the flexibility to alter traversals, particularly as mission goals change over time. He argued that initially human missions to Mars will resemble Apollo, with pre-determined sites of interest; however, with longer mission durations, new sites of interest will be added. This strategy shift is similar to the on-going MER exploration. Thus, traverses later in the mission will be focused on solving new problems (Carr, 2001). In the Cone Crater EVA analysis, Carr identified key variables for planning excursions: visibility, transportation costs (including metabolic expenditures) between waypoints, "accessibility map" or "reachability map", and communication ability with 'home' mission controllers (Carr, 2001; Carr, Newman, & Hodges, 2003).

Clancey (2001) conducted an ethnographic study of activities within the Haughton-Mars Project (HMP) research camp, a Mars-analog site[1]. His main objective was to understand how astronauts may live and work on Mars. With regards to excursion planning, he described it as a group activity, involving assessment of multiple representations, such as satellite and aerial imagery of the area. The scientists felt that time, date, explorers, location of exploration, and purpose of exploration were the key descriptors of the field excursion. Clancey noted differences between the scientists in the way they chose to explore, particularly biologists and geologists. Biologists and geologists rarely traveled together as they had few sites in common, and biologists visited fewer sites than geologists. Clancey concludes that biologists' search is "depth-first" while a geologists' search is "breadth-first".

Based on these terrestrial analog studies, additional critical planetary EVA variables that affect path planning are summarized in Table 3.3. Both Carr and Clancey emphasize the nature of human exploration, where current information leads to new sites of interest and how explorers collaborate to come up with a plan. These reports overlap with the already presented Apollo and MER review, hence only few, new variables are listed. Nonetheless, these studies establish a method for using terrestrial analogs a means for acquiring operational requirements for future planetary EVAs.

[1] Haughton-Mars Project site is discussed more in a subsequent section.

Table 3.3 Planetary EVA variables based on terrestrial analog studies

Variable Category	Variable Specifics
Astro-agent	Expertise of astronaut
Goals	Flexibility to add new sites
Exploration costs	Visibility (line of site), reachability
Infrastructure	Communication infrastructure (e.g., beacons)

3.3.3 OBSERVATIONAL STUDY: MARS-ANALOG EXCURSIONS

In support of this thesis and to further investigate future planetary EVAs, an observational study of excursions was conducted at the Haughton-Mars Project (HMP), a terrestrial Mars-analog research site set in an uninhabited island, high in the Canadian Arctic. HMP is sponsored by NASA and the Canadian Space Agency (CSA) and managed by the Mars Institute. They host an international, interdisciplinary group of scientists and engineers who return yearly within the operational season, a period of 5 to 6 weeks.

The site is located next to Haughton Crater (Figure 3.3), a 38 million year old impact crater on Devon Island (75ºN, 90º W). The area is of interest due to the geological similarities to the Martian terrain. Due to the remoteness of this Mars-analogue terrain, exploration-like activities can be undertaken by geologists and other scientists. Thus, excursions conducted at this site resemble sorties of long-duration planetary space missions. Assessing and reviewing HMP excursions can provide insight to the potential problems astronauts may face in future planetary EVAs.

Figure 3.3 Haughton Crater, Devon Island, Canada. Area of crater excursion highlighted.

During the 2005 season[1], eight excursions (Table 3.4) were categorized through an "EVA Log". Excursions were varied as researcher at the camp had objectives they wanted to accomplish within the time they were stationed at HMP. For example, one observed traversal was conducted by two geologists on foot to a near-by, known location while another included a large group on all-terrain vehicles (ATVs) to an unexplored destination. Some traversals observed included researchers wearing a mock space suit, provided by Hamilton Sundstrand. Creating an "EVA Log" permitted a systematic assessment of each excursion.

Using the log, each excursion was documented through a combination of: a) observation of pre-excursion planning session and post-excursion debriefings, b) pre- and post-excursion interviews with excursion participants in addition to observations taken from actual excursions. Multiple methods were implemented in order to best capture as many excursion experiences as possible without interfering with preparation for and execution of the excursions. Aside from the "EVA Log", other excursion documentation analyzed included digital audio recordings and extensive notes taken during planning meetings, interviews, and debrief sessions. When possible, digital imagery was used to also characterize the excursion. A hand-held GPS receiver was used to track the traversed path and indicate waypoints for two of the observed excursions, with limited success.

For each "EVA Log", the traverse leaders described the following parameters that described their excursion: goals, total estimated time, participants, number of sites visited, type of mobility to sites, estimated distances between sites, and expected environmental factors that could affect the excursion. Additionally, an inventory of supplies was recorded and the excursion planning session was summarized. After the excursion was performed, the leaders' debrief included unexpected events that triggered re-planning.

Table 3.4 summarizes all the excursions that were documented. There were varied excursions, involving as little as two people or as many as ten. Site selection was typically based on the scientific goals of the excursion. The exception to these were traversals that were akin to technology testing, such those involving the mock spacesuits. The type of mobility used was determined by the

[1] The duration of the observational study was only ten days.

distance between camp and exploration sites. The debriefs were essential in understanding the factors that triggered re-planning, and how expectations differed from what actually occurred in the excursion. While eight observed excursions may not seem many, the variety of observations enables an assessment of that is rich in information, providing insight to future human planetary exploration.

Table 3.4 Summary of all HMP excursions observed during 2005 season

	1	2	3	4	5	6	7	8
Goal	Sample collection Trinity Lake	Prototype space suit test	Sample collection, image survey, gravity measures	Prototype space suit test, gravity measures	Reconnais-sance excursion for suit testing	Gully survey along coast line	Geological observations Terrain assessment	Haughton Crater revisit, sample collection
Time	3 hours	1 hour	4 - 5 hours	2 hours	4 - 5 hours	6 hours	3 - 4 hours	4 hours
People	2, geologists	10, mixed	4, researcher + security	4, mixed	6, researchers + security	9, mixed	2, geologist	9, mixed
Sites	1	1	6	5	not specified	5	1	1 fixed
Mobility	ATV, walk	ATV, walk	ATV, walk	ATV, walk	ATV	ATV	ATV, walk	ATV
Planning	Repeat site, preset road. Naïve and experienced pair.	Repeat site, preset road. Mix of naïve and experienced people.	Planning of sites: order, prioritization. Expected terrain difficulties. Unique opportunity.	Repeat site, preset road. Naïve and experienced pair.	Areas of interest identified. One researcher to wear suit, majority naïve people.	Traversing > 20 kms in unexplored area. Maps crucial. Many naïve people.	Large time to accomplish time, short time of travel.	Accomplish sample collection that had been postponed. Other areas of interest identified.
Post-notes		2.5 hours	Unexpected delays due to terrain. Postponed one site. Extra walking. 6 hours.		2.5 hours. Equipment repairs done along way.	Several delays due to terrain. Large group traveled slowly. > 6 hours excursion.		Large group of naïve travelers, terrain delays.

3.3.3.1 DETAILED EXCURSION EXAMPLE: INTO HAUGHTON CRATER

One HMP excursion (#3 in Table 3.4) is described in detail below in order to illustrate a traversal and its similarities to Moon and Mars sorties.

This rare excursion into the middle Haughton Crater was the first of the 2005 season, as special permission is required to enter the crater. There were four participants in this excursion, of which three were experienced scientists that had visited the area several times in previous years. Each researcher had a clear objective: 1) taking gravity measurements at multiple sites, 2) conducting a gully survey, or 3) collecting soil samples at one particular site. These objectives are part of a longitudinal, on-going investigation of Haughton Crater, and are critical for the prolongation of HMP as a research site. The fourth person in the excursion was a safety officer (necessary protection in case of polar bears – a hazard exclusive to Arctic exploration).

A couple of hours before the start of the excursion, all participants gathered to finalize the plans. While the traverse leader was in charge of the meeting, there was open communication between all parties involved. Each researcher outlined his objectives for the traverse, identifying specific sites they wished to reach (Table 3.5). Furthermore, each site was prioritized. They used maps, both topographic and aerial, to determine a feasible route. This was accomplished rather quickly as all three scientists had previously undertaken similar routes in past seasons. Hence, they were also able to anticipate a few locations along the path that would be difficult to navigate. The meeting ended with safety considerations, securing essential items, like radios and ATVs, in place.

The participants initially planned to visit six sites using the ATVs. During the planning session, the scientists delineated which sites were most critical and necessary, and settled on a preliminary route to follow (Figure 3.4). The traverse leader estimated a total of 4 to 5 hours to complete the excursion, based on the number sites, estimated time to reach each and time spent at each site. Additionally, this excursion was also unusual in the respect that there was a real time-pressure element. Two of the researchers were leaving HMP that evening on a flight that could not be delayed. Most excursions at HMP did not have this time pressure as there was no real cost involved with returning to camp late.

Table 3.5 Summary of sites and estimated parameters for Haughton Crater excursion

Site	Tasks	Path Distance	Travel Time	Reached?
Junction	Gravity measure	7 – 8 km	20 – 30 min	√
Tripod Hill	Gully survey, Gravity measure	7 – 8 km	20 min	√
Old Base Camp	Soil sample	4 km	15 min	X
Anomaly Hill	Gravity measure	7 – 8 km	30 min	√
Perseverance Hill	Gravity measure	< 1 km	5 min	√
HMP Base Camp	Gravity measure	13 - 14 km	35 min	√

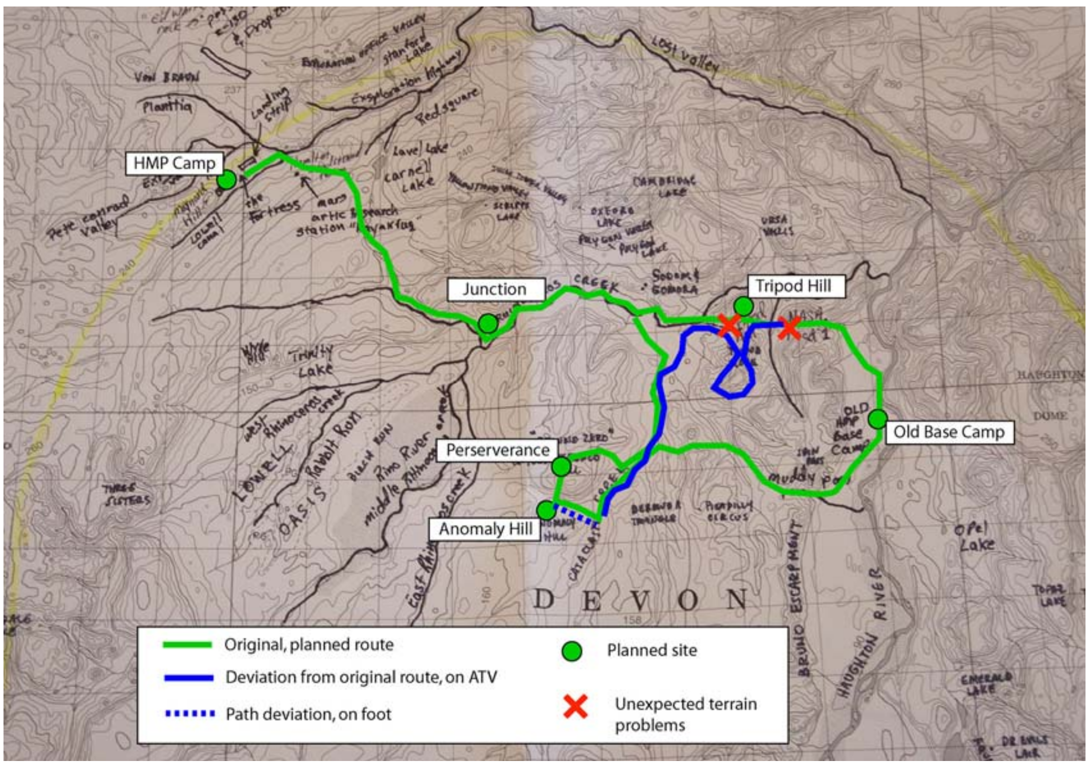

Figure 3.4 Haughton Crater excursion, with planned path, sites, and deviations from route.

A detailed inventory of their supplies was recorded. Their supplies fell under three categories, which were common to all excursions at HMP: excursion, critical and scientific supplies. Excursion supplies included lunch, while critical supplies were items that were related to safety, such radios and repair tools for their mobility (i.e., ATV) like a tire pump. Scientific equipment was carried that directly mapped to the objectives of each researcher, and included a gravimeter, cameras, hand-held GPS receiver, and sampling tools.

After the excursion (Figure 3.5), the traverse leader discussed events that triggered re-planning. Due to the wet weather earlier that season, the ground bearing strength of certain areas had decreased, making it very difficult to drive over. Since this was the first incursion into the crater that season, they had not anticipated the terrain conditions would be that poor. The traverse leader estimated that they had spent all together over an hour extricating their ATVs from two separate locations. These locations were relatively early in the route and were not the anticipated problem areas. The excursion participants were left to re-assess their plan and schedule.

Figure 3.5 Haughton Crater excursion images

The first re-planning event was with Old Base Camp, the only site where soil samples were to be collected. It was unreachable with ATVs due to the low ground bearing strength. Walking was too time-consuming as there was a pressing need to return to base for the evening flight. Unfortunately, the alternative route to the site the researchers had selected was infeasible due to a terrain miscalculation. Thus, for this traversal, the researchers left out the essential site, in hopes that a future opportunity would arise to return and collect the necessary samples.

The second re-planning event was at Anomaly Hill site (Figure 3.4), where the researchers opted to walk to the site as the terrain was too weak to support ATV travel. While walking was time-consuming, it was still feasible within the time constraints. Eventually, the researchers all returned to camp in time for the two departing scientists to catch their flight. The excursion (summarized on Figure 3.4) took a total time of about six hours.

3.3.3.2 IMPLICATIONS OF HMP OBSERVATIONAL STUDY

There are many important analogies that can be drawn from HMP excursions. These traversals are more complex than Apollo EVAs, involving a greater number of people, trekking farther and through much more difficult terrain. On the other hand, HMP is an established ground research site, and though remote, does not necessitate critical life-support equipment such as spacesuits[1]. Regardless of the differences with the Apollo program, similar problems arise, such as leveraging different types of mobility and incurring delays due to terrain uncertainty.

The additional planetary EVA variables gained from the observed HMP excursions are summarized in Table 3.6. These variables played a role in determining paths, both at the pre- and re-planning stages. While providing insight to longer duration missions, this study emphasized the terrain (and environment) as one of the main sources of uncertainty. With respect to the environment, weather played an important role, particularly as to how it affected the terrain itself. In turn, the terrain uncertainty (e.g., actual ground bearing strength) affected path planning *and* re-planning. Plans took into account potential problem areas, while unanticipated ones triggered re-planning. Furthermore, the selected transportation modes (ATV or rovers) interact with the terrain differently, affecting speed and power consumption. Combining different modalities of transportation (e.g., walking vs. driving) and being able to switch during the traverse increased the likelihood of completing all the

[1] It could be argued, though, that the safety officer, protecting against polar bears, is a life-critical element.

mission goals. Overall, the HMP observational study was essential in the identification of planetary EVA variables that would affect path planning under circumstances that go beyond Apollo, in particular, long duration lunar stays and Mars human missions.

Table 3.6 Planetary EVA variables based on HMP observational study

Variable Category	Variable Specifics
Astro-agent	Effect of mixed and large teams; experience (particularly for re-planning)
Goals	Task-specific equipment (e.g., mass)
Terrain	Landmarks, waypoints; emphasis on ground bearing strength
Transportation	Reliability of; trade-offs between walking and driving; emphasis on interaction between transportation and terrain & environment
Environment	Emphasis on recent past weather affecting future terrain conditions
Infrastructure	Communication availability (interaction with terrain & environment)
Consumables	Total time available
Operation rules	Drive-back requirements (e.g., alternative configuration of ATV and explorers), safety-critical supplies (e.g., mass), continuous communication availability, operationally required communication stop
EVA components	Alternative plans

3.4 FUTURE EVAS: BEYOND APOLLO EXPERIENCE

Based on subject-matter expert interviews and the NASA (2005) "Exploration Systems Architecture Study" (ESAS), there are additional planetary EVA variables that are relevant to the planning and re-planning of excursions. The variables summarized (Table 3.7) pertain to the types of missions that have yet to be accomplished: long duration human missions on the Moon and Mars.

Table 3.7 Planetary EVA variables based on planned future human missions

Variable Category	Variable Specifics
Goals	Scientific return (value) of task and sites, repeatability
Terrain	In-situ materials, remote sensing information (e.g., morphology, chemistry), new sensed data (increasing fidelity)
Transportation	Other types (pressurized rovers, campers), preparation time
Environment	Radiation
Infrastructure	Bases, refueling stations, navigation system (e.g., global, inertial)
Consumables	Life cycle of equipment
Operation rules	Radiation limits, day/night restrictions, work-hours limits,

The durations of EVAs will impose additional time limitations that are driven by total work conducted by astronauts, acceptable radiation exposure per EVA, and restrictions on night-time traversals. Mission architecture will determine the availability of other modes of transportation (e.g., pressurized rovers), refueling stations, and navigation systems. The longer the mission, the more information is acquired, and higher fidelity models will have to be incorporated into the planning of excursions. Even though these extended-stay missions are only at the conceptual design stage, important variables that will affect planetary EVA planning and re-planning can be identified and incorporated into the Planetary EVA Framework.

3.5 PLANETARY EVA FRAMEWORK

The proposed framework for planetary EVAs was derived based on the case studies described, such as the Apollo program, on-going robotic planetary exploration, and HMP Mars-analog excursions. The variables, identified in detail within each case study, were re-organized into input categories or outputs (Table 3.8). The output is an optimized (or satisficing) EVA plan that meets the goals of the mission and constraints. The mission and operational constraints are based on system boundaries, which are imposed by the resources and operational procedures. The framework organizes these variables and constraints that affect and determine the planning and re-planning of future planetary sorties.

The framework presented in Figure 3.6 is only a graphical representation of the identified variables that need to be accounted for in a complete decision support aid for human planetary exploration. Thus, the Planetary EVA Framework proposes the information requirements for such an aid, and is not meant to be a comprehensive representation that specifies interactions (e.g., linear vs. non-linear relationships between variables), nor temporal constraints that are mission or context dependent. The use of a Venn diagram in Figure 3.6 is utilized to illustrate that the nested constraints are based on multiple sources, and the relationships between variables will be defined by a priori models (e.g., exploration costs and terrain).

Table 3.8 Categorization of planetary EVA inputs and outputs

Type	Group	Variable categories
Input	Mission Resources	Astro-agent Transportation Infrastructure Consumables
	Mission Objectives	Goals: sites, tasks
	Safety Margins	Operational rules
	Physical Environs	Terrain Environment
	Models	Exploration costs: consumable rates
Output	EVA Plan	Path Schedule Other costs along path Contingencies

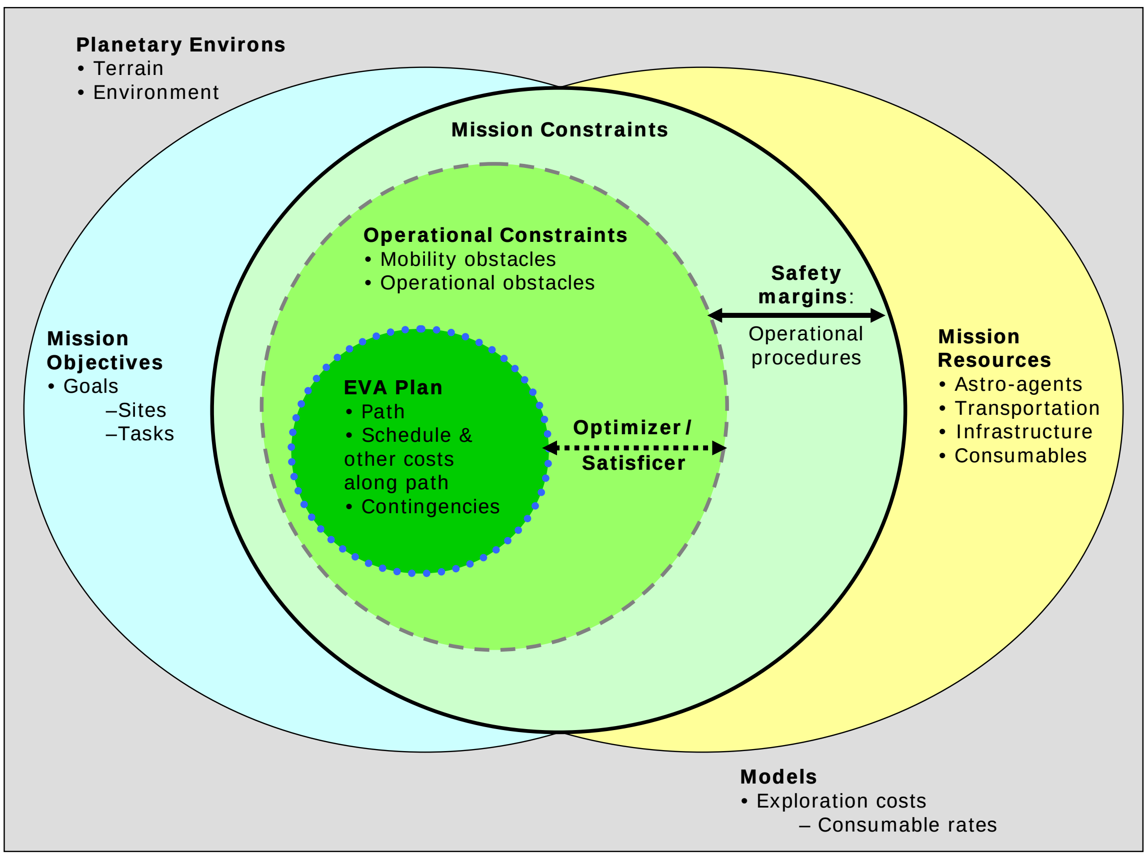

Figure 3.6 Planetary EVA Framework

3.5.1 INPUTS

The input categories of a planetary EVA are mission resources, mission objectives, safety margins, exploration cost models, and planetary environs. Defining each of these is necessary to develop a complete decision support aid from EVA planning and re-planning.

Every EVA is conducted within a particular planetary environ, in this case, Moon or Mars, and includes terrain and environment models. With respect to the terrain, vital characteristics that pertain specifically to path planning are elevation, slopes, rock density, rock size, and ground bearing strength. Other information, for example, chemical composition, would be more relevant for the selection of scientific sites. With respect to the environment, important models include lighting conditions (for Moon) and dust storms (for Mars). The terrain plays an important role in mission planning and re-planning as it is one of the main sources of uncertainty, as exemplified in the Apollo EVAs, current MER experience, and HMP excursions. Decreasing terrain uncertainty can be achieved by increasing the fidelity of terrain maps. It is important to consider the uncertainty of all models because all EVA plans will be based on these assumptions, and thus, any model errors will inevitably introduce errors in the plans.

The mission objectives, or goals, are the sites and tasks that need to be accomplished in a single EVA. These goals drive the planning of the EVA. Location, associate tasks, and priority are key characteristics of the mission objectives. The goals of an EVA are not always fixed, as additional sites and tasks may be incorporated to take into account new discoveries or emergencies. Thus, it is also imperative to know associated time and energy expenditures for specific tasks during re-planning.

The mission objectives can only be met if the appropriate mission resources are in place. The resources are the elements available to carry out the EVA, including the astro-agents, the transportation modes, the infrastructure, and the consumables. The term astro-agent is used because future (and current) planetary exploration encompasses both humans and robotic agents. Each astro-agent will have a particular capability or expertise that might be necessary to accomplish the EVA mission. Potentially, a source of uncertainty may be the effect of mixed teams on accomplishing an EVA, which may add unexpected delays.

Transportation is a key element in all planetary EVAs, and the advantages of different locomotion options (e.g., walking or driving) need to be exploited to maximize mission success. Several examples within the case studies cited reveal a poor understanding of the relationship between the transportation mode and terrain, resulting in re-planning of excursions. Therefore, it is important to understand how the mobility type interacts with terrain characteristics (e.g., speed under different terrain rock densities).

EVA planning and re-planning will have to also take into consideration the infrastructure in place on the planetary surface, be it a lander, a base, or even re-fueling stations. The type of communication and navigation system available is essential for any real-time exploration aid. It is important to determine if these systems interact with the terrain or the environment in order to model these relationships in the planner.

The fourth mission resource is the available consumables. The type and amounts of consumables will be determined by the selected astro-agents for the EVA mission (e.g., oxygen for humans versus power source for robots). Among the mission resources, consumables are most important as it is these that drive mission constraints, discussed subsequently.

The relationship between EVA inputs (mission objectives and resources) and the planetary environs is defined by the exploration cost models. These cost function models would determine (or predict) traversed distances, durations of tasks (be it walking, roving, or working), energy consumed (e.g., metabolic rates or power used), rate of consumables expended, and favorable environmental positions. Many cost functions are needed, as they are astro-agent and/or transportation specific, yet few models exist. Reliable estimates of exploration costs (in particular time and energy consumed) are crucial for the planning of complex EVAs, as miscalculations will force in-situ re-planning.

3.5.2 CONSTRAINTS AND OUTPUTS

The intersection of mission objectives and resources is designated as the overall mission constraints. Mission constraints are akin to hard constraints, absolute limitations imposed on the system. For instance, the astronaut cannot consume more oxygen than the fixed amount available. Other limitations involve the type of transportation used in the EVA, and relate, for example, to the maximum speed of the mobility or terrain that is physically traversable.

A subset of the mission constraints are the operational constraints, which are similar to soft constraints as they are delineated by established operational procedures, or safety margins. Soft constraints are ones that can be violated but are imposed on the EVA for precautionary reasons. For example, one type of rule may be that astronauts should not exceed a particular metabolic rate during the traversal. Another type of safety margin is one where an astro-agent must always return to base with 10% of their consumables remaining. Mission planners will have to use the exploration models to assess if the EVA plan violates any of the operational procedures. Safety margins may possibly be overly conservative estimates (e.g., total radiation dosages) due to limited operational experience of human planetary exploration, resulting in safe, but inefficient EVAs.

Two types of operational constraints are identified: mobility and operational obstacles. Mobility obstacles depend on the type of transportation used, and is further restricted by safety margins. An area may be inaccessible by a rover because the rock density in that area is too high, yet that same location could be explored on foot (at the cost of additional time, for example). Incomplete knowledge of how different transportation modes interact with the terrain will result in poor calculations of obstacles, and hence affect path planning.

Operational obstacles are areas are out-of-bounds due to operation rules. For instance, future EVAs may not permit exploration of areas that are out of communication range. If using a rover, "walk-back" requirements limit the maximum traversable distance from base or re-fueling station. In terms of re-planning, it would be necessary to classify when these operational restrictions can be violated, i.e., in case of an emergency.

Every EVA mission must satisfy the mission goals and constraints. As a result, the EVA plan outputs a path with an associated schedule and other exploration costs. Ideally, contingency plans should also be outlined for rapid re-planning (e.g., alternative routes to sites or back to base). Predicting associated exploration costs at sites and along path is imperative as it is this information that will be compared to the actual EVA. Real-time discrepancies will indicate reasons for re-planning. Over time, comparative analysis between predictive and actual exploration costs will assist in developing more accurate models of the cost functions, terrain, environment, and their interactions with transportation modes.

3.5.3 APPLICATION OF PLANETARY EVA FRAMEWORK

The Planetary EVA Framework is a result of comprehensive assessment of the past, present and future human-robot planetary exploration. All the identified variables affect the planning and re-planning of extra-vehicular activities. Mission resources and objectives determine the mission constraints. These are further narrowed down by the imposed safety margins, resulting in operational constraints. Only within the system boundaries can an EVA plan be defined, including a path with adjoining schedule and other costs. This framework is also broad enough that, with a few nomenclature modifications (e.g., astro-agent), it could apply to other domains that involve multiple types of agents and missions that require planning and scheduling. This includes unmanned ground or air vehicles, rescue teams, and diving expeditions. The specifications of each input category and constraints have to describe though the work domain for that particular field, just as the Planetary EVA Framework addresses human traverses on extra-terrestrial surfaces.

Before sending humans to explore Moon and Mars, we need to have a clear understanding of the relationships between inputs and constraints across all type of planetary EVA architectures. Acquisition of this knowledge will not only serve the purpose of developing EVA planning decision support aids but also modeling future planetary surface operations with implications for logistics mission planning. While additional specification with respect to the parameters and constraints is possible, the proposed Planetary EVA Framework is the first step in establishing a common ground to discuss human-robot extravehicular activities. For the purposes of this thesis, only a small sub-section of the framework is applied for the developed prototype EVA path planner.

4 PATH PROTOTYPE: A DECISION SUPPORT AID FOR LUNAR & PLANETARY PATH PLANNING

4.1 DEVELOPING A PATH PLANNER PROTOTYPE

In order to investigate how humans conduct path planning optimization with computer support, a prototype automated path planner was developed. A subsection of the Planetary EVA Framework (Figure 4.1) was selected to develop the path planner aid. From the mission resources, the aid considers traverses that are accomplished on foot by a suited astronaut. Six exploration costs were chosen with corresponding models that interacted with the lunar terrain model. A specific area on the lunar surface is used, and sites involve pre-determined locations that astronauts must reach. In terms of the environment, the only variable considered is sun position. Operational constraints imposed were purely based on the interaction between mobility type and slope (and hence, terrain elevation). The decision aid concerns itself with the *path* plan output. While this might be considered a limited subset, the selected scenario resembles the early Apollo missions, and potentially, the first human missions back to the Moon. In addition, the path is a fundamental component of any EVA sortie as it determines all exploration costs (like oxygen consumed) and establishes the schedule. The prototype path planner aid is the basis from which a more complex and complete decision support aid for planetary exploration can be developed. It is a generic interface that could be applied to other path planning domains beyond human planetary exploration. There are only a few inputs that are specific to Lunar exploration, of which all are interchangeable, thus, applicable to Earth and Mars.

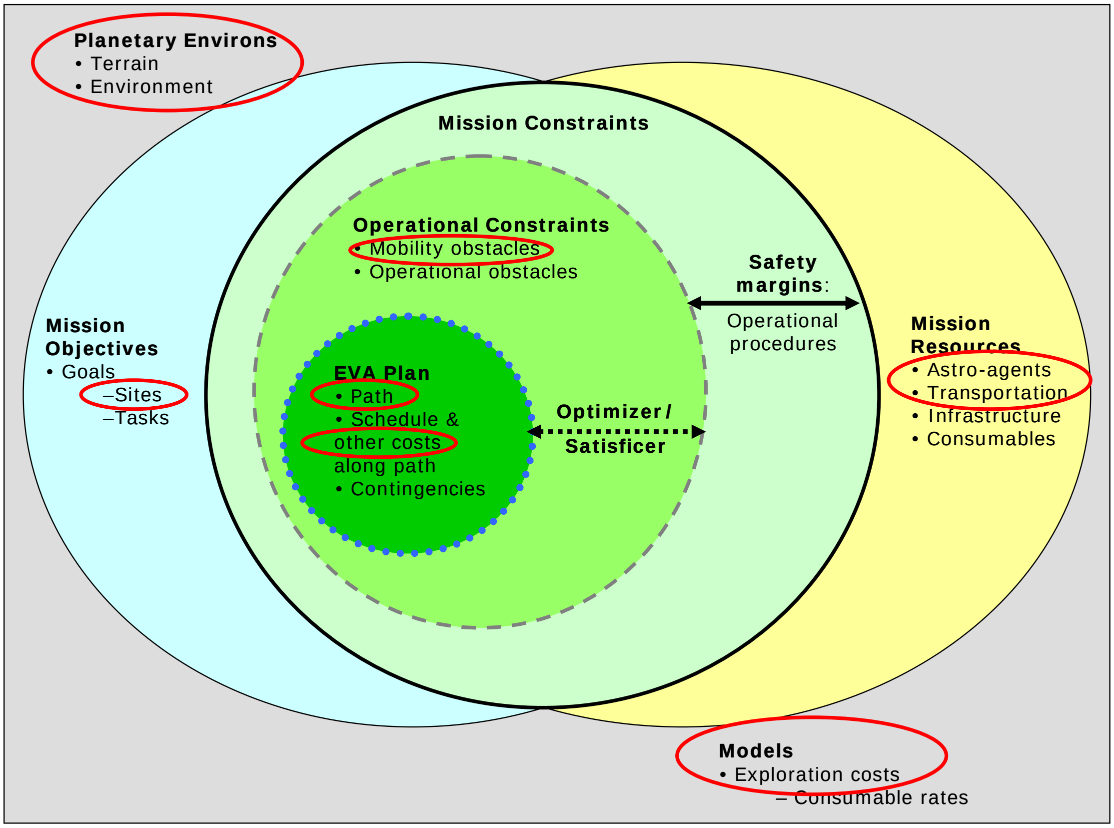

Figure 4.1 Subset of Planetary EVA Framework applied to prototype decision support aid

This chapter describes the developed path planner, its features and interface specifics. The prototype, named PATH (Planetary Aid for Traversing Humans, Figure 4.2), was developed over the course of a year and is written in Java (version 1.5). The path planner has as inputs a terrain map, an obstacle map, cost function models, and other environmental conditions. There are two methods in which a path can be defined: 1) either the user manually makes the entire path, or 2) the automation generates portions of the path. PATH also provides the users with the capability of always manually modifying paths. There are three possible map visualizations that have been developed and tested. Finally, PATH's interface, which includes tables and tabs, was modified between experiments, and hence, there two interfaces are described. All of these PATH features (e.g., maps, cost functions, visualizations) are explained in detail in this chapter.

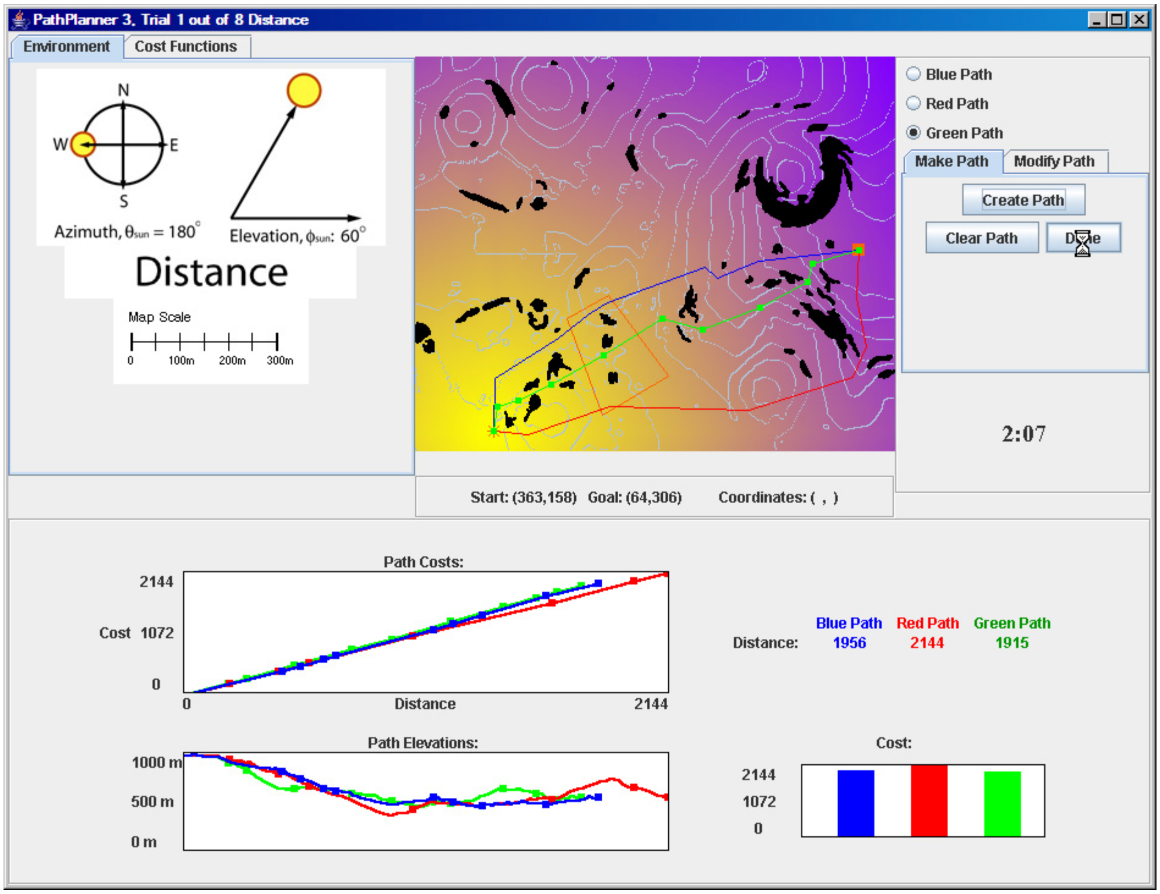

Figure 4.2 Prototype path planner, PATH (Planetary Aid for Traversing Humans)

4.2 TERRAIN MAPS

This section includes a description of the path planner's inputs: a terrain elevation map and an obstacle map. Each is pre-defined by the experimenter. Within the scope of this research, two terrain maps were used, based on lunar terrain data. This component of the path planner is interchangeable, as the experiment can define any elevation and obstacle map.

4.2.1 CONE CRATER: APOLLO 14

While global mappings of the Moon are available, high resolution terrain maps of smaller areas are scarce. In a previous study (Carr, 2001), Carr interpolated a 5-meter resolution elevation map of the Apollo 14 landing site of Cone Crater (about 3.65° south, 17.47 ° west on Moon), an area roughly

3.2 km^2. While there are other explored areas on the Moon that have more varied and interesting terrains, high resolution elevation maps either do not exist or are not accessible. Furthermore, this Cone Crater area was a site that has already resulted in a problematic expedition (Apollo 14). The area is marked by the large crater on the north-east corner, including high elevations around the southern-face, and low elevations on the western portion of the map (Figure 4.3).

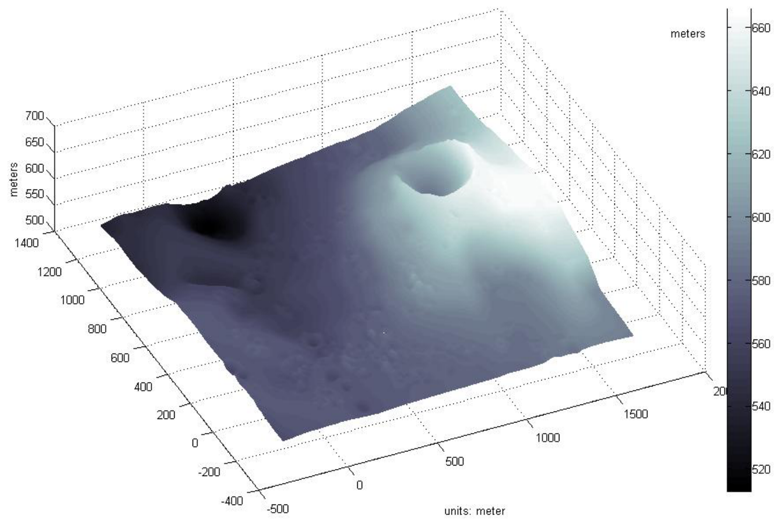

Figure 4.3 Three-dimensional map of original Cone Crater area, terrain used on PATH

This original terrain map, as depicted in Figure 4.3, was used in the first set of experiments. Subsequently, the terrain was deemed as not having enough changes in slopes and limiting the choice of trials for experimentation. A modified version of the terrain map was generated (Figure 4.4). Based on the original elevation maps of the Cone Crater area, additional small craters and "mole-hills" were inserted on the elevation maps. The changes not only allowed for more diversity in trial choice, but also increased the complexity of each trial such that there was not always one clear best path.

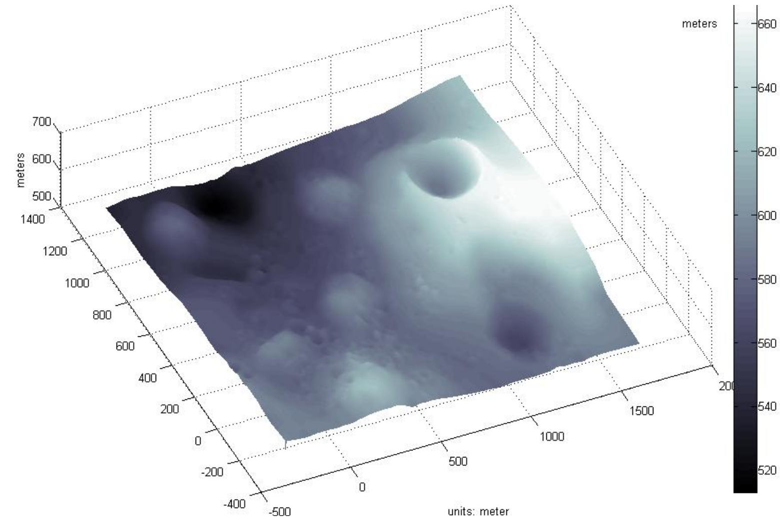

Figure 4.4 Three-dimensional map of modified Cone Crater area, terrain used on PATH

4.2.2 GENERATING OBSTACLES

The obstacles used in the path planner are strictly based on terrain slope. Figure 4.5 depicts these obstacles for the original and modified Cone Crater terrains. If the slope at a particular point was too steep for a suited astronaut, it was considered an obstacle. A conservative slope angle was selected, 15 degrees, as the maximum slope suited astronauts could climb or descend. During the Apollo program, spacesuits were pressurized and bulky, thus greatly limiting the astronaut's mobility. If a point was surrounded by steep terrain (such as the bottom of a crater), this area became inaccessible, and thus, also an obstacle. While other types of obstacles are possible (such as terrain that is too rocky to traverse), PATH restricts itself to one type of obstacle based on terrain slope.

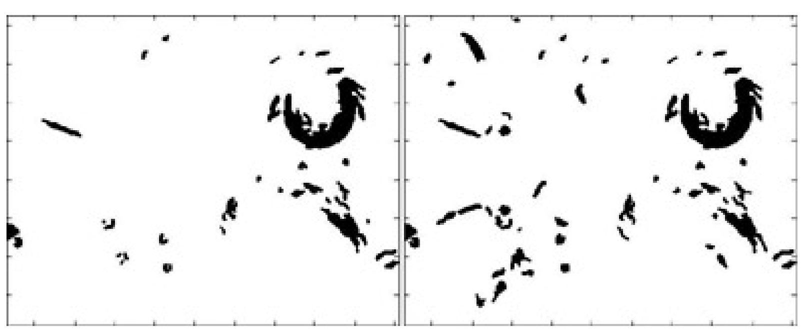

Figure 4.5 Obstacles (slopes greater than 15 degrees) for terrain maps used in PATH. Left, original Cone Crater terrain; right, modified Cone Crater terrain

4.3 COST FUNCTIONS MODELS

PATH also takes as input a selected cost function (or objective function) which determines a path's cost. Every generated path has an associated cost. The most commonly used cost function within path planners is distance. For PATH, any cost function is permissible, as long as it grows monotonically (i.e., the cost from one point to another is always greater than zero) and is independent of path history (i.e., the cost function does not change along the path). These constraints are a consequence of the type of search algorithms implemented in PATH. A total of six cost functions were tested in two different experiments: Elevation Score, Sun Score, Distance, Time, Metabolic Cost, and Exploration Cost. Each is subsequently described in the following sections.

4.3.1 SUN SCORE AND ELEVATION SCORE

Surface visibility is a key factor in the success of lunar sorties. In particular, sun glare was an issue during navigation (both on the rover and on foot) and scientific observations. If the sun is directly in front of the astronaut, there is too much glare to look forward (Figure 4.6). On the other hand, if the sun is directly behind the astronaut, there could be exaggerated, misleading shadows, obscuring the real size of slopes and obstacles. A low sun elevation (angle above the horizon) will likely result in large shadows and the sun at "high noon" will create no shadows. It is thus most favorable, for perception and navigation purposes, if the sun does not create glare but still provides some shadows on the terrain.

Figure 4.6 Sun glare when returning to the lunar module (NASA image: AS14-67-9367)

In order to quantify favorable sun positions, Carr created a cost function, Sun Score, that assessed the sun position along the path trajectory (Carr et al., 2003). The Sun Score[1] (SS), Equation (1), is a function that takes into account the relative azimuth angle, θ, and the relative elevation angle, ϕ, between the sun and the observer (Figure 4.7). Equation (2) defines θ, which is the difference between sun's azimuth angle (θ_{sun}) and the observer's orientation ($\theta_{observer}$) relative to East (0 degrees). Equation (3) defines ϕ, which is the difference between the sun's elevation angle (ϕ_{sun}), and the terrain slope the observer is at ($\phi_{observer}$).

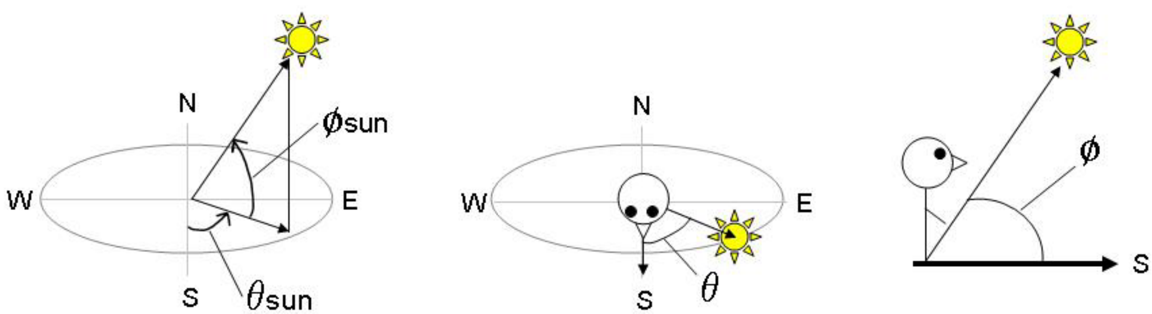

Figure 4.7 Sun position angles (left), relative azimuth angle (center) and relative elevation angle (right)

With respect to the Moon, the sun's elevation and azimuth angles are considered fixed over the course of one EVA (about 8 hours) as the rotation period of the Moon is 28 days (as opposed to 24 hours like on Earth). The Elevation Score, ES (4), is a subset of the Sun Score, only taking into account elevation angles. Ultimately, a high Elevation or Sun Score means that the lighting condition is not ideal, while low scores indicate better lighting conditions for traversing. The optimal sun angle is that which causes the most contrast across the surface, which is when the sun is high in the sky (approaching 90 degrees in relative latitude) and at a cross angle from the direction of travel (at 90/270 degrees in relative longitude). If required to walk towards the sun, the best direction of travel is 45 degrees in relative longitude.

---

[1] Carr's original Sun Score ranged from 0 to 1. However, the cost functions implemented have to grow monotonically, and thus, the function was adjusted to take this into account.

$$SS = (\cos(2\theta) + 2) \cdot (\cos(2\phi) + 2) \quad (1)$$

$$\theta = \theta_{sun} - \theta_{observer} \quad (2)$$

$$\phi = \phi_{sun} - \phi_{observer} \quad (3)$$

$$ES = \cos(2\phi) + 2 \quad (4)$$

4.3.2 DISTANCE

The cost function of Distance is based on actual distances between points on the map and is dependant on the map resolution. For example, the terrain maps used had a resolution of 5 m, thus a lateral motion would be a distance of 5 meters while a diagonal one, would be about 7.07 meters. The shortest distance is achieved through a straight-line path, while avoiding obstacles.

4.3.3 TIME COST

The Time cost function is equivalent to duration of the sortie: how long does it take an astronaut to get from one location to another. The Time cost function incorporates both distance and terrain slope (one more variable than the Distance function).

While several studies have predicted, measured, and simulated lunar walking speeds, unfortunately, there is very little data that relates astronaut traverse velocity with terrain slope. For example, Stone (1974) estimated from Apollo 11 video that astronauts traversed at a maximum speed of 2.5 m/s, though most of the speeds are under 1 m/s. During Apollo 17, an average of 0.75 m/s was used to calculate the "walk-back" requirement (Jones, 1995). Apollo 15 measured maximum speeds of 0.61 m/s, but this was based on walking short distances around the lunar lander or at geological stops (Jones, 1995). Minetti predicts that the optimal walking speeds on Moon will be 0.6 m/s and the walk-to-run-transition speed is 0.8 m/s (Minetti, 2001).

Waligora and Horrigan (1975) have the only published data from the second EVA during Apollo 14 that relate actual distance traveled, duration, and net elevation change on the lunar surface. The data they published is plotted in Figure 4.8. Astronauts during this EVA were had a range of walking speeds between 0.4 – 1.6 m/s, walking fastest on flat terrain. The net elevation change is over hundreds of meters in distance, so these velocities are only averages. Even though the data points are scarce, it appears that velocities dropped faster over positive terrain slopes (i.e., uphill) while over negative terrain slope (i.e., downhill), velocities decrease at a slower rate.

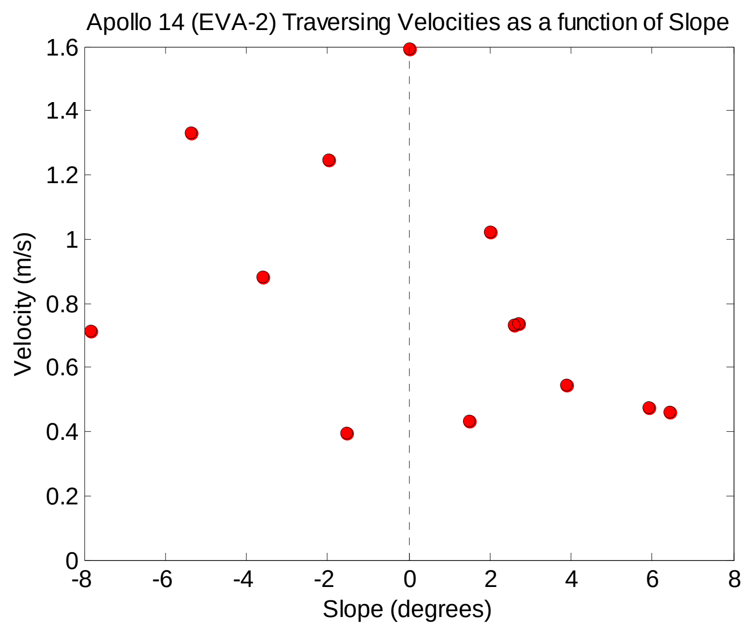

Figure 4.8 Apollo 14 EVA-2, walking velocities, from Waligora and Horrigan (1975) data set

A velocity profile for the Time cost function was developed that resembled the Apollo 14 velocity data (Figure 4.9). This profile is defined by Equation (5), where v is velocity in m/s and α is slope in degrees. The maximum velocity is 1.6 m/s and occurs at flat terrain. Going downhill is faster than going uphill. Time, Equation (6), is calculated by multiplying velocity by the distance traversed.

$$v = \begin{cases} 0.095 \cdot \alpha + 1.95, & \text{if } \{-15 \le \alpha < -10\} \\ 0.06 \cdot \alpha + 1.6, & \text{if } \{-10 \le \alpha < 0\} \\ -0.02 \cdot \alpha + 1.6, & \text{if } \{0 \le \alpha < 6\} \\ -0.039 \cdot \alpha + 0.634, & \text{if } \{6 \le \alpha \le 15\} \end{cases} \tag{5}$$

$$\text{Time} = v \cdot \text{Distance} \tag{6}$$

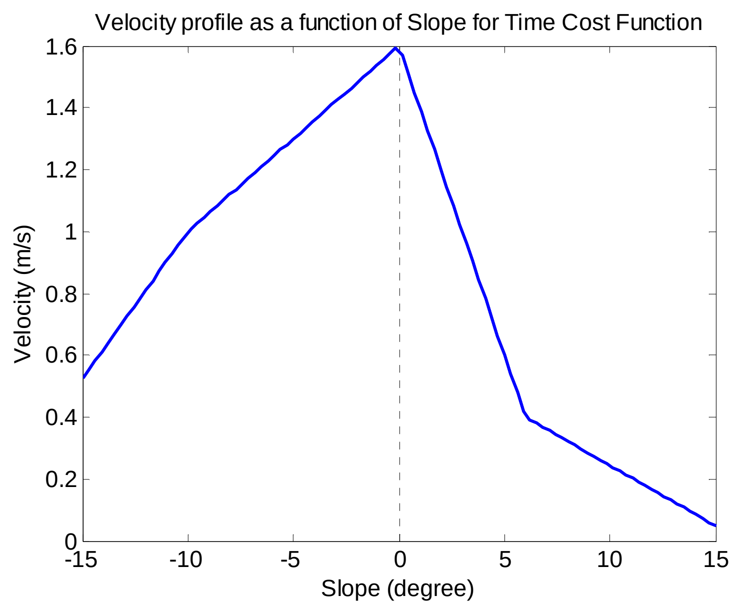

Figure 4.9 Velocity profile as a function of slope for Time Cost Function

4.3.4 METABOLIC COST

The Metabolic cost function is a measure of how much energy is consumed by the astronaut while traversing on the lunar surface. The Metabolic cost function builds upon the preceding function, and thus, integrates distance, terrain slope, and velocity information.

Several studies have predicted and simulated energy consumption rates while traversing on the lunar surface (Newman, Alexander, & Webbon, 1994; Stone, 1974; Wickman & Luna, 1996; Wortz & Prescott, 1966). These are summarized in Figure 4.10. In order to make comparisons across these studies, energy consumptions rates were transformed to Joules/second, assuming the Wortz and Prescott study's average weights and velocities, and if necessary, average oxygen consumption energy. In general, these estimates are not far from the average EVA metabolic rates on the lunar surface (Figure 4.11), which was 273 ± 32 J/s (Waligora & Horrigan, 1975). Unfortunately, most of studies do not correlate the rates with terrain. Studies by Stone (1974) and Wickman and Luna (1996) provided metabolic cost models, but the latter does not include the effect of terrain slope.

Only the Apollo 14 data for EVA to Cone Crater correlates metabolic rates with terrain slope and velocity (Waligora & Horrigan, 1975), which can be used to assess metabolic cost models.

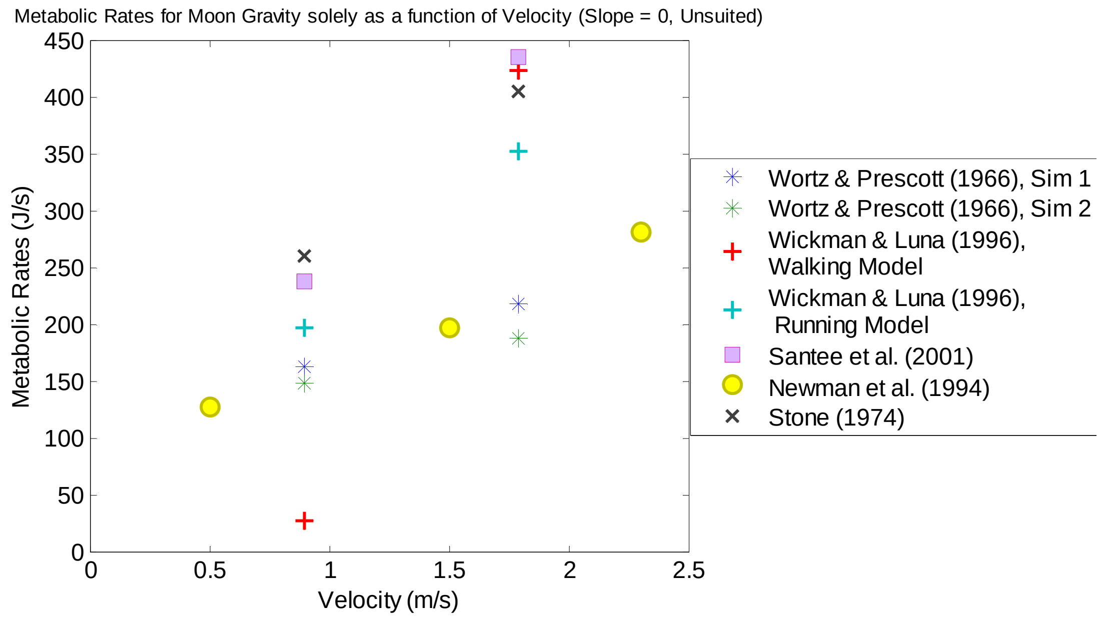

Figure 4.10 Summary of lunar metabolic rates as a function of velocity (on flat terrain)

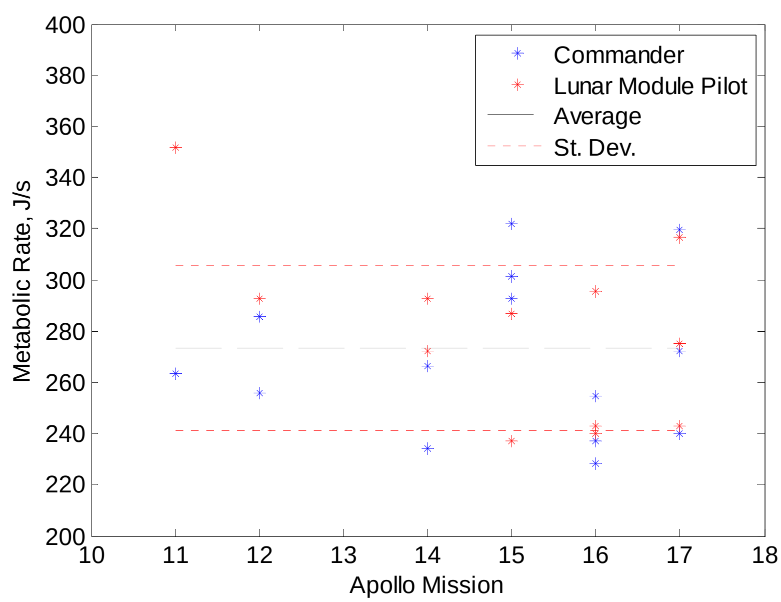

Figure 4.11 Average EVA metabolic rates of astronauts during Apollo missions (data from Waligora and Horrigan, 1975)

There were two models considered for the Metabolic cost function, one by Stone (1974) and the other by Santee et al. (2001). Stone's model, Equation (7), is a function of velocity (v in km/hr) and α, slope in degrees. This model is based on simulated lunar traverse experiments, i.e., a fitted curve (Figure 4.12, left). It is interesting to note the trends exhibited by the model: there are high metabolic cost penalties uphill but not as much as going downhill.

$$\text{Energy rate} \;=\; 115 + (0.45 + 1.26 \cdot \sin\alpha + 2.23 \cdot \sin^2\alpha) \cdot 100 \cdot v \tag{7}$$

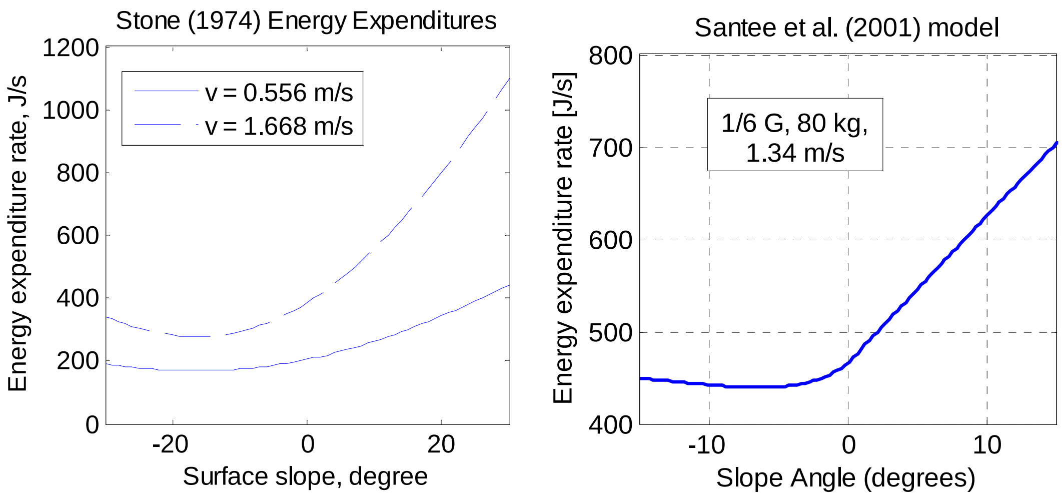

Figure 4.12 Lunar energy consumption rates: left, Stone (1974) model and right, Santee et al. (2001) model

Santee et al.'s (2001) model, Equation (8), is based on both experimental data and physical walking models. The energy rate model is broken into two main components: energy to move forward, Equation (9), and energy to move up- or downhill, Equation (10). Both components depend on velocity, v in m/s, and the mass, m in kg, of the person traversing. The energy to walk up- or downhill is a function of both velocity and slope, α in degrees. Even though Santee's model was not developed for extra-terrestrial navigation, the model has a gravity factor (in m/s^2), thus, it can be used for modeling energy rates for the Moon and Mars. Figure 4.12 (right) plots the energy rates predicted for the lunar case (at a fixed velocity). It is noteworthy to highlight that it exhibits the same trends as the Stone model (low rates downhill, high rates uphill).

$$\text{Energy rate} = W_{level} + W_{slope} \tag{8}$$

$$W_{level} = [(3.28) \cdot m + 71.1] \cdot [(0.661) \cdot v \cdot \cos(\alpha) + 0.115] \tag{9}$$

$$W_{slope} = \begin{cases} 0, & \text{if } \alpha = 0 \\ W_{up} = 3.5 \cdot m \cdot g \cdot v \cdot \sin(\alpha), & \text{if } \alpha > 0 \\ W_{down} = 2.4 \cdot m \cdot g \cdot v \cdot \sin(\alpha) \cdot 0.3^{|\alpha|/7.65}, & \text{if } \alpha < 0 \end{cases} \tag{10}$$

In order to determine which energy consumption rate model to use, the models were compared to actual Apollo 14 energy rates for the Cone Crater EVA (Figure 4.13). Apollo 14 EVA velocity and corresponding slopes (from Waligora & Horrigan, 1975) were used to predict metabolic rates using the Stone (1974) model and the Santee (2001) model. These were plotted against actual energy expenditure rates from the two astronauts on the EVA. On downhill slopes, Santee's model is conservative (overestimates rates) while Stone's model underestimates rates. On uphill slopes, Santee's model predicts higher rates than Stone's model, but both seem to underestimate rates. Carr showed that these discrepancies are due to the fact that astronauts were dragging a small science cart, and other than this, Santee's model was a good estimator of walking lunar metabolic rates (Carr, 2001). For this reason, and because Santee's model has a gravity factor and is more conservative than Stone's, it was used in the PATH prototype, in combination with the Time Cost function to form the Metabolic Cost function model for PATH, Equation (11). In this model, there are high metabolic cost penalties for going uphill as opposed to downhill (Figure 4.14).

$$\text{Metabolic Cost} = \text{Energy Rate} \cdot \text{Time} \tag{11}$$

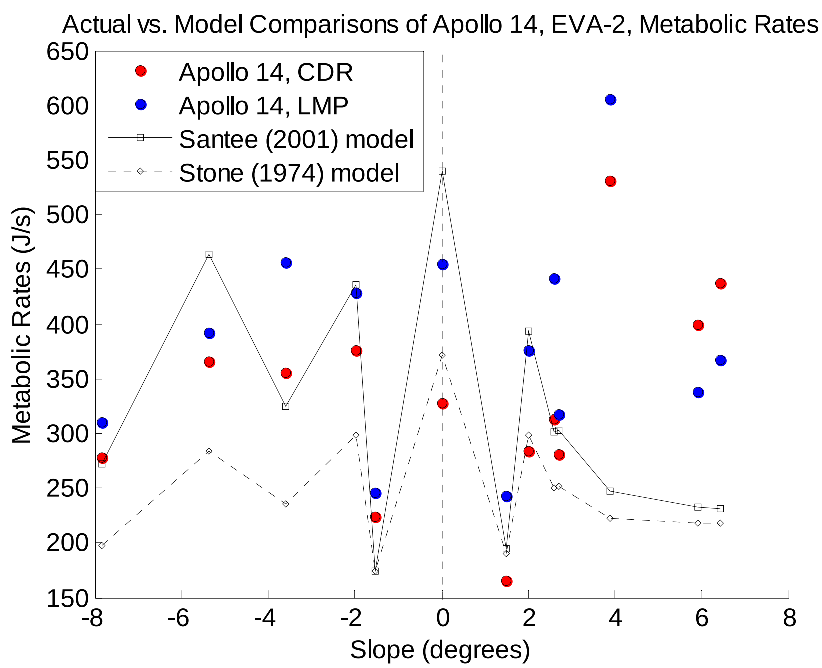

Figure 4.13 Metabolic rates for Apollo 14 EVA-2 compared to modeled rates

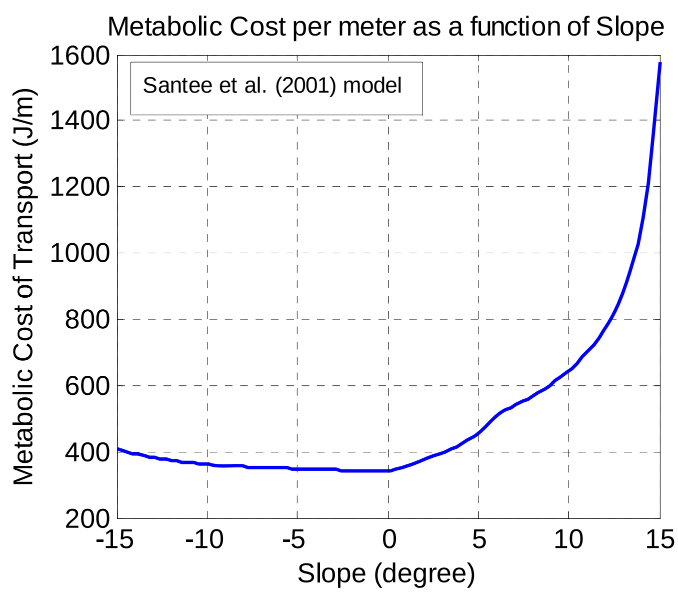

Figure 4.14 Metabolic cost (per meter) as a function of slope, using Time Cost

4.3.5 EXPLORATION COST

The Exploration Cost is a cost function that takes into account all the preceding cost functions, integrating distance, terrain slope, velocity, and sun position information. Exploration Cost is the combination of the Metabolic Cost function and the Sun Score. Sun Score is weighted against the Metabolic Cost. A 1:2 ratio was selected to indicate that Metabolic Cost is more important than Sun Score (sun position) as energy consumed is directly related to oxygen supply (and hence, safety critical). The weighting is also a ratio that PATH users could intuitively understand (i.e., Metabolic Cost is twice as important as Sun Score).

$$\text{Exploration Cost } = (\text{Metabolic Cost}) \cdot \left(1 + 1/2 \cdot SS\right) \tag{12}$$

4.3.6 INCREASING COMPLEXITY OF COST FUNCTIONS

The set of cost functions presented depend on each other and grow in the number of variables. For instance, the Elevation Score only a function of the relative elevation angle, ϕ, and the Sun Score builds on Elevation Score with the addition of relative azimuth angle, θ. These two cost functions are tested in the first experiment. Distance, Time, Metabolic, and Exploration functions have a similar relationship (Figure 4.15). This set of functions is tested in second experiment. The Time cost function introduces the additional variable of slope. In the Metabolic function, velocity becomes a more important factor, though it still depends on the same variables that determine Time (slope and Distance). The Exploration cost function captures all possible cost functions by including both Sun Score and Metabolic Cost. This relationship between functions is important because during path planning, different cost functions represent an increase in numbers of variables manipulated, and hence a growing task complexity.

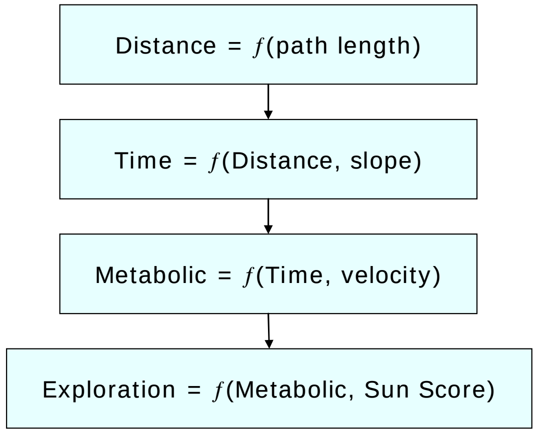

Figure 4.15 Flow and interdependences between cost functions

4.4 AUTOMATION LEVELS

There are two methods that a PATH user can define a path, given start and goal locations. These correspond to two automation levels, LOA 2 and 4 (see section 2.2.1). Currently, only one automation level at a time can be used. LOA 2 represents the condition in which computer aid is used primarily as a filtering tool, and the human does most of the problem solving, while with LOA 4, the automation, after prompting by the user, suggests a solution, leaving the problem solving mostly to the computer. These two levels of automation reflect the human-computer function allocation, in other words, how much of the path is decided by the automation or the human. For the purposes of this research, these levels have been renamed passive and active automation (LOA 2 and 4, respectively) corresponding with the role automation plays within the path planning task.

Within active automation, the user only decides on an intermediate point between the start and goal locations, while the automation generates least-costly path segments (Figure 4.16, left). Users are restricted to only placing their intermediate waypoint within a pre-determined critical way-area. Within passive automation, the user takes a more central role, deciding all the waypoints within a path (Figure 4.16, right), while the automation takes the more supportive role of calculating all the costs. These levels are described in more detail subsequently.

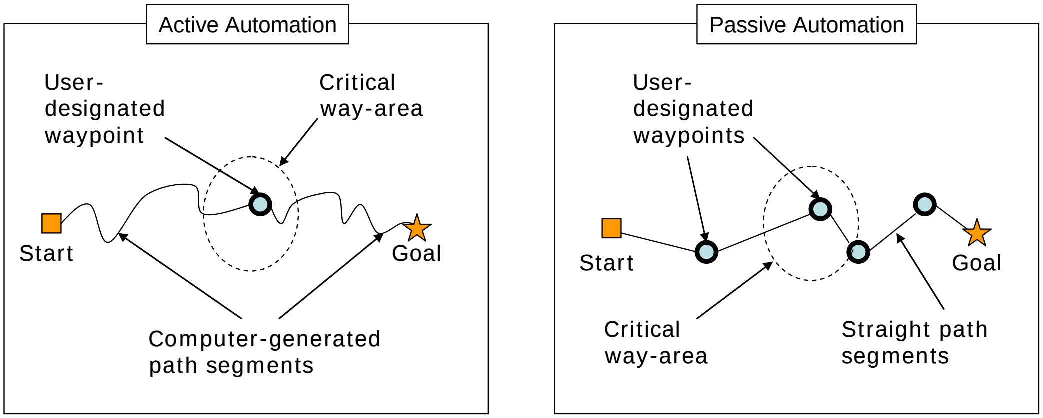

Figure 4.16 Difference between active (left) and passive (right) automation

PATH initially starts out with the experimenter selected inputs (e.g., terrain map, cost function) and a start, goal, and critical way-area. The critical way-area is an area on the map of interest (see orange polygon outline in Figure 4.2 and dashed outline in Figure 4.16) and represents a potential site that an astronaut wants to explore. Every path must cross through this way-area when using PATH.

With respect of the interface, the only visual difference between passive and active automation is found on the far right of the interface (Figure 4.17). Within passive automation, the user must click on "Create Path" button before starting a path; this informs the interface that the user is going to make a series of waypoints that define a path. The user then selects waypoints on the map terrain which are connected by straight path segments. Once the goal is selected as a waypoint, the path is completed. Within active automation, the user must make a waypoint in the critical way-area and then click on "AutoPath". The automation then calculates and plots a least-costly path from the start to that waypoint and from the waypoint to the goal. With the inclusion of the way-area, the problem space remains relatively large, permitting the exploration of different automated paths.

The algorithm used to find least-costly paths is the numerical potential field method, NPFM (Barraquand, Langlois, & Latombe, 1992; Rimon & Koditschek, 1992). NPFM is applied to a discrete map, i.e., a grid space. PATH's terrain map is a discrete map, where every grid cell (which are 5 meters apart) is associated with a terrain elevation. In general, the path planning algorithm first calculates the minimum total path cost from every grid cell to a pre-determined goal location. The minimum cost at the goal is zero. In order to determine the least-costly path from a pre-determined start location, a gradient descent search is applied from the start grid cell, ending at the global minima – the goal grid cell. Further details, advantages and disadvantages of the algorithm are discussed in a subsequent section (section 4.7). The least-costly path (a sequence of grid cells from the start to the goal) is smoothed using the midpoint line algorithm (Breseham, 1965), creating the path segments. This algorithm approximates a straight line between grid cells.

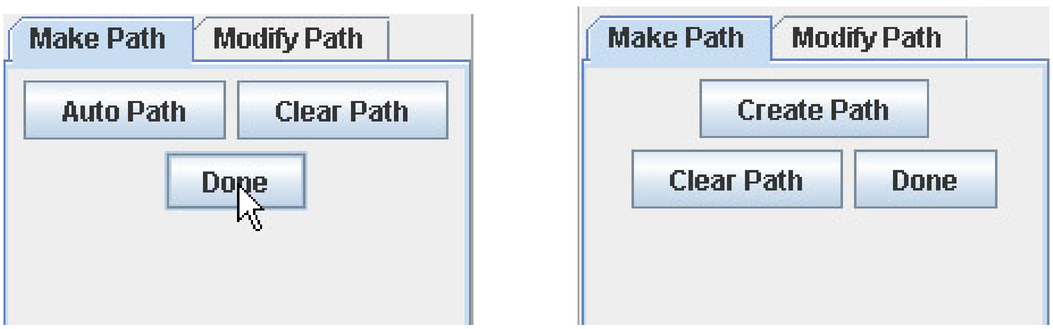

Figure 4.17 Active (left) and passive (right) create path buttons on the PATH interface

The "Done" button (Figure 4.17) indicates the user has finished creating their path, and the selected path is submitted as the least-costly path.

4.5 MODIFYING PATHS: SENSITIVITY ANALYSIS TOOLS

Once a path is defined, either through passive or active automation, the user is able to modify paths. Currently, only three paths can be seen at once in the PATH interface (Figure 4.2); each is color coded for easy distinction (blue, red, and green). While the user is not limited to the number of paths they can make, only these colored paths can be seen and manipulated. In order to create multiple paths, PATH gives the users the capability of clearing entire paths (with "Clear Path" button, Figure 4.17) or modifying paths through the "Modify Path" tab functionalities (Figure 4.18). Once a path is selected (either by clicking on the path itself on the map or selecting the path's corresponding radio buttons, which are on the top-right corner of PATH interface, Figure 4.18), the user can move waypoints, add waypoints and delete waypoints. In order to put into effect the cost changes of the modified path, the user must click on "OK" under the "Modify Path" tab. Users can utilize the "Cancel" button[1] to undo a path modification (before pressing "OK").

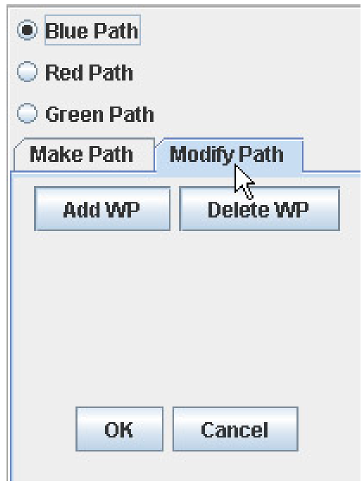

Figure 4.18 Modify path functionalities and path radio buttons

Once the "Modify Path" tab is selected, the user can move waypoints (by clicking and dragging waypoints on the map terrain). The "Add WP" and "Delete WP" buttons are to add and delete path waypoints; they are toggle buttons, and pressing them activates and de-activates these functionalities. Users can only add new waypoints on the path. Once these are added, they can be moved and deleted as well. Only if the modified path is obstacle-free will users be able to update the path's cost. A warning is given to the user that he/she needs to keep modifying the path until it is obstacle-free.

In summary, there are two basic modes the user can be in when modifying paths: moving or adding/deleting waypoints. One can distinguish which one they are in by either observing if the "Add" or "Delete" buttons are depressed or by noting the cursor type. When moving waypoints, the cursor is a cross-hair; when adding or deleting, the cursor is a pointed hand.

[1] Users cannot revert to a previous path after "OK" is pressed.

4.6 PATH DISPLAY FEATURES

4.6.1 PATH COST INFORMATION

Once a path is made or modified, path information is displayed in the bottom section of the PATH interface. The basic information provided includes the path cost of each individual path, the paths' costs along waypoints (cost profile), and the paths' elevation profile. There are two versions of the path information displayed, each corresponding to the two experiments conducted using PATH. The difference between the first and the latter is the inclusion of cost bar graphs.

The first version of path information display includes a table with total path costs, a path cost profile graph, and a path elevation profile (Figure 4.19, where two paths are shown). The table at the top has three columns, one for each color-coded path; there are two rows, one for the total Distance of the path and the other for the cost based on the cost function (in the case of Figure 4.19, Sun Score). Below the table, a cost profile is plotted. The color matches the corresponding path color. This plot provides information as to how the path cost is changing along course of the path (x-axis is always Distance, while the y-axis is the particular cost function). The end points of the path cost profiles are the same total costs represented in the table. Finally, below the path cost profile is the path elevation profile, which plots the elevations the path encounters. Again, colors match the corresponding path. If no path exists, no information is displayed, as in the case of the "green" path in Figure 4.19.

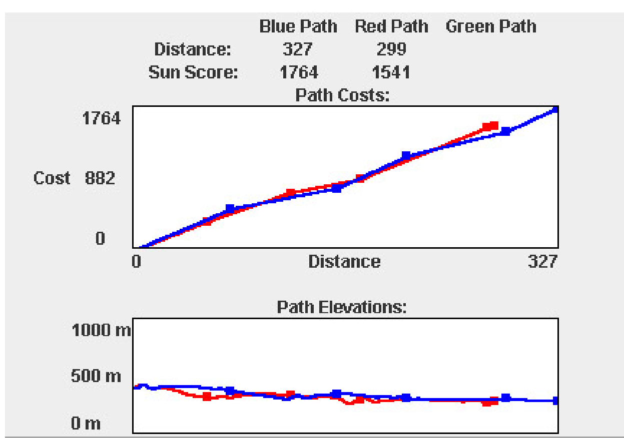

Figure 4.19 Path information display, version 1

For the second version of path information display, a cost bar graph was included and color was added to the table of costs (Figure 4.20). The path cost profile and the elevation profile is still included but is shifted to the left to allow for the table and the cost bar graph. Color was included in the table in order to match the profiles. A cost bar graph, which has the same information as table (total path cost), was included after users asked for a quick way of determining which path created had the minimum path cost. Color was again implemented for ease of recognition.

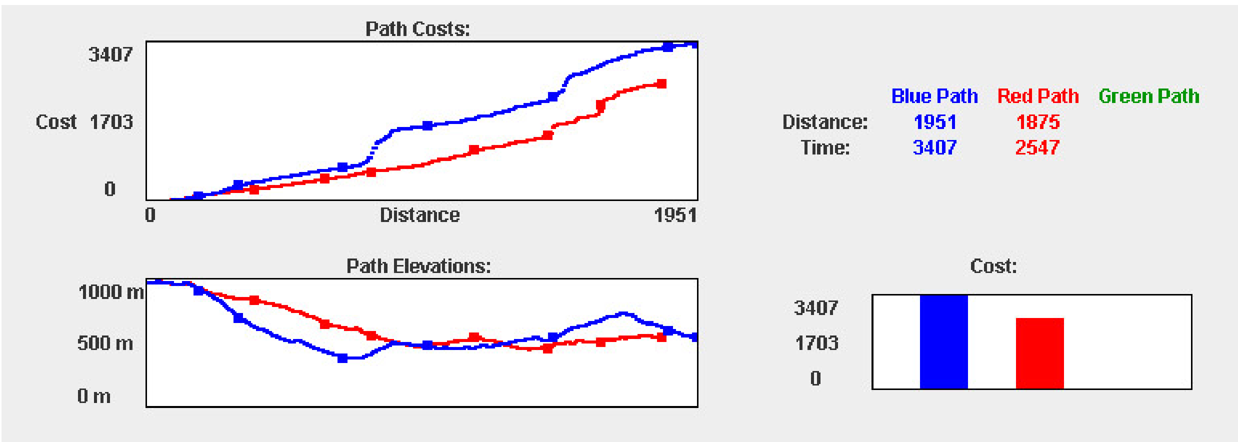

Figure 4.20 Path information display, version 2

4.6.2 Other Display Features

On the left side of the PATH interface, information about sun position, cost function, and map scale is displayed (Figure 4.21). In the first experiment, only two cost functions were tested. Their descriptions fit in the "Environment" tab, which also includes sun position (azimuth and elevation angles, both numerically and graphically). However, for the second experiment, a more complex set of cost functions were tested. Since the functions are interdependent, all cost functions had to be described. Therefore, the second interface version of PATH included a "Cost Functions" tab (Figure 4.21). Finally, a map scale is included for completeness.

In the second version of the PATH interface, a timer was shown on the far right of the display (see Figure 4.2 for location of timer). This timer was an indicator for the user on how long they had been path planning[1].

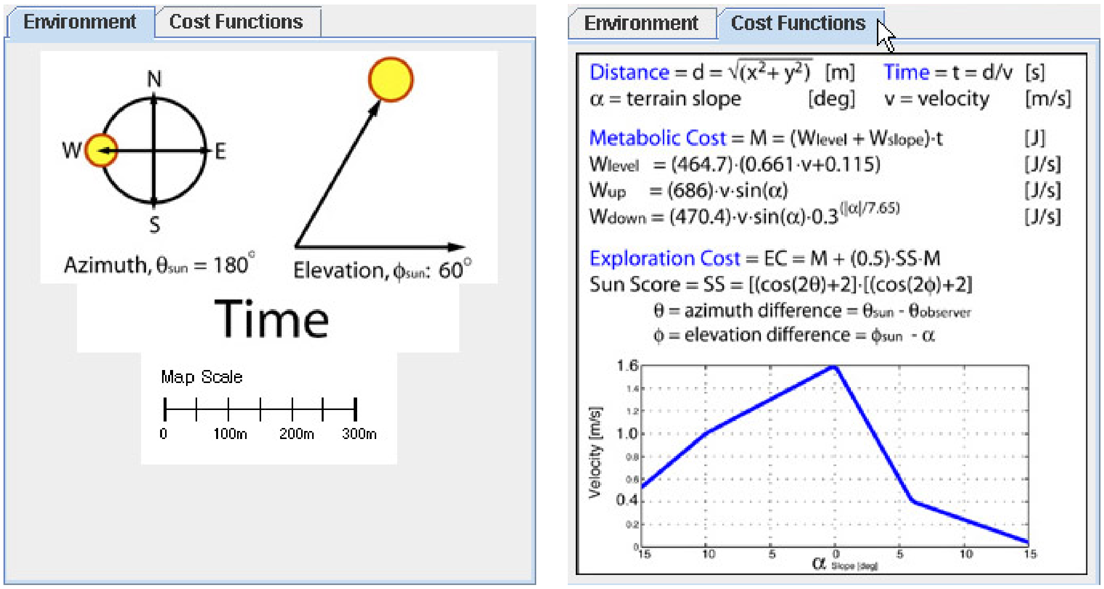

Figure 4.21 PATH display of sun position and cost functions

4.7 MAP VISUALIZATIONS

There were three possible map visualizations: elevations contours, levels of equal cost (LOEC) visualization, and elevation contours with LOEC. Initially, these visualizations were optional, i.e., they could be triggered on/off by the user. However, currently, these visualizations are fixed and only one can be seen at a time.

[1] Timer was included as part of the second experimental protocol.

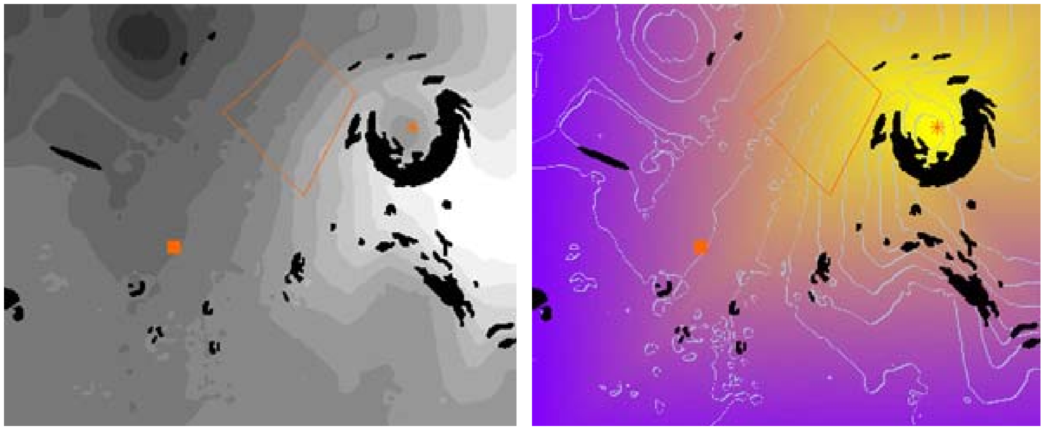

Figure 4.22 Map visualizations that include elevation contours. Left, grayscale-filled contour map; right, contour lines overlaid on top of the second visualization

The elevation contours visualization, as its name implies, provides elevation information such that within each contour, the elevation is relatively the same (within 10 meters). There are two ways in which elevations contours were shown in PATH: grayscale-filled contour map and contour lines overlaid on top of levels of equal cost visualization (Figure 4.22). For the grayscale map, white is the highest elevation while dark gray is the lowest elevation (black remains obstacles). The elevation contours presented in the visualizations resemble topographical maps, except there are no raw elevation markings. This design decision was chosen because it was deemed the addition of numbers would clutter the map and that the detailed information is provided in the path elevation profiles.

4.7.1 Levels of Equal Cost Visualization

The levels of equal cost (LOEC) visualization (colored gradient in Figure 4.23) displays integrated information about areas on the map that have relatively equal cost. LOEC is based on the calculations generated from the numerical potential field method (NPFM), which is the algorithm used in the active automation version. The NPFM requires a grid decomposition of the space (or terrain), which is based on the map resolution. Each location on the map is a grid cell with a matching terrain elevation. Obstacles are also pre-determined, and the corresponding grid cells are labeled as obstacles before the algorithm solves for a minimum path. Path costs are calculated based on a cost function. Each of these elements (map resolution, obstacle identification, and cost function accuracy) is set in advance, and thus, the visualization representation is only as good as the a priori knowledge available.

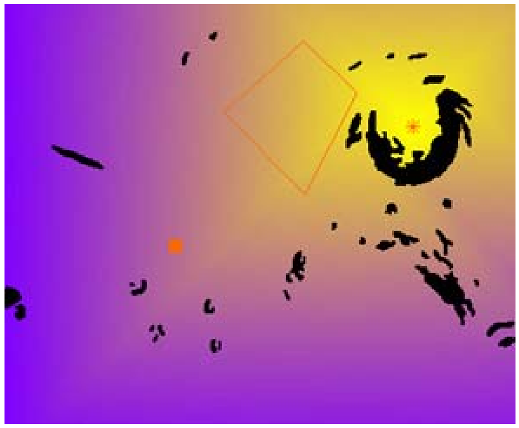

Figure 4.23 Levels of Equal Cost (LOEC) visualization

The LOEC visualization colors are based on the grid cell's minimum total cost from that location to the goal. The grid cell's minimum total cost can be calculated because the terrain, obstacles and the cost function are known a priori and pre-determined. In order to calculate this minimum total cost for each grid cell, a goal location is first selected and given a zero cost. Then the path cost of traversing from a grid cell to the goal is computed. The cost between grid cells is determined by the cost function (fixed experimentally). All possible paths from a grid cell to the goal are attempted but only the minimum total cost is saved. Essentially, this process is similar to implementing Dijkstra's (1959) algorithm, which is an exhaustive search of total costs from every "node" (in this case, grid cells) to a reference "node" (with NPFM, the goal grid cell). With respect to obstacles, each is given a high penalty cost, thus minimum costs associated with obstacles are always high.

As a result, each grid cell has a corresponding minimum total cost that is relative to the goal. Together, these costs can be considered a minimum total cost field (similar to a potential field) where the goal location is the lowest point (with a zero cost) and obstacles are peaks of high cost. Since this cost field is relative to the goal (i.e., the minimum cost from any location to the goal), the visualization is a static map as long as the goal remains the same. The minimum total cost field is rendered in color, and locations depicted in the same color have the same minimum total cost to the goal – thus color indicates equal levels of cost. The color gradient chosen is between yellow and purple, as they are complementary colors[1], and thus, create the most contrast when side-by-side, helping users discern between different cost levels.

In order to further describe the process of generating the LOEC visualization, a simple illustration of how a total cost map is calculated is seen in Figure 4.24. The map is defined as a grid space, where the cells representing obstacles are seen in black. A start and a goal cell are pre-selected, depicted in Figure 4.24 as “S” and “G”. The minimum total cost from a cell to the goal is calculated based on the pre-selected cost function. In this example, the cost function is the Manhattan distance (i.e., no diagonal motions from cell to cell). All the minimum total cost values relative to the goal are stored and these are the costs that are represented in the LOEC visualization. For instance, in Figure 4.24, all the cells with minimum cost of “5” would share a color. In order to determine a least-costly path, one searches for the next smallest minimum cost until the goal is reached (i.e., a gradient search). In the example presented, only one optimal path is highlighted even though there are many possible least-costly paths that lead to the goal. This same minimum cost map can be illustrated in 3D (Figure 4.25), where the peak cells are the obstacles.

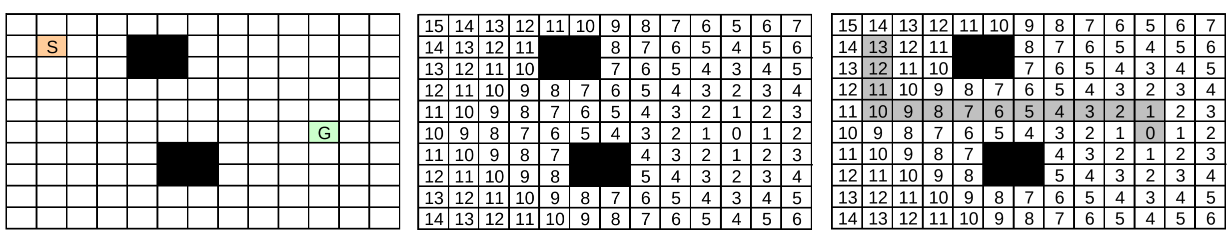

Figure 4.24 Illustration of LOEC generation. Top: (left) grid map with start & goal; (middle) complete cost map; (right) an optimal path

[1] Additionally, these colors were chosen because they did not overlap with the existing red, blue, and green paths.

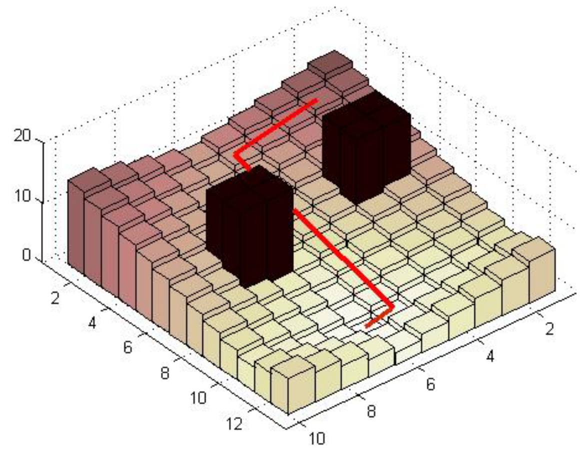

Figure 4.25 3D illustration of LOEC generation

The rationale behind developing the LOEC visualization is multifold. First, as mentioned, the visualization is based on the algorithm (NPFM) that determines the least-costly path between a start and goal location. Thus, this visualization illustrates the computations calculated by the path planner in order to ascertain an optimal path. The computations take into account all the variables and the underlying cost function, which may be a complex model. In turn, users can draw upon this visually summarized, integrated information to help them determine a path, regardless of the number of variables and the complexity of relationships between variables (which will be discussed subsequently in detail).

Second, the notion of "equal costs" is similar to the elevation contours, where a contour line (or area) represents relatively equal terrain elevations. A contour map is a common, 2D graphical representation of changes in terrain elevations that is familiar to most people, thus, PATH users could extend the same metaphor to minimum total costs. A color map was preferred over contours lines (or areas) because it was deemed that this representation would provide more granularity (i.e., the user could distinguish more levels of equal cost than with contour lines). An alternative visualization was considered based on the minimum total cost field: a cost gradient map visualization. Since the minimum cost from every location is known, the "cost slope" (the gradient of the cost at a particular location) could be calculated and displayed (a 2D spatial derivative of the minimum total cost field). This gradient map of cost was contemplated as a possible visualization but it was considered to be an uncommon graphical representation, and likely unintuitive and difficult for users to interpret. Furthermore, some directional information could not be captured in a gradient map.

Third, the particular algorithm implemented, NPFM, fundamentally relies on the idea of a "force field metaphor" (Frixione, Vercelli, & Zaccaria, 2001) and hence, leverages direct perception interaction (Gibson, 1979). There are several path planning methods that could have been used to find least-costly paths (e.g., applying a visibility or a Voronoi graph in conjunction with a search algorithm like A*). The NPFM was applied because it combines cell-decomposition space and artificial potential fields for planning (Khatib, 1986). The potential fields was deemed particularly useful for human-computer interaction since it fundamentally relies on the idea of that path solutions are "attracted" by the goal location and "repelled" by obstacles.

This underlying metaphor that is the basis of the visualization provides human decision makers an intuitive, perceptually-based solution for a large problem space. Hence, the visualization leverages on direct perception interaction, an important display design principle and of particular relevance in decision aids for complex domains. According to Gibson, direct perception is a process that requires little inference and relies on lower levels of cognitive control. If the human decision maker utilizes perception to solve the problem (i.e., "pushed" a complex problem solving task to a lower level of cognitive control), it could produce superior performance (Vicente & Rasmussen, 1992). The reason behind this is that users may potentially develop a realistic mental model of the system and its constraints, resulting in more correct decisions that are done quickly. The concept of supporting direct perception is also present in ecological interface displays, which Rasmussen (1999) ascertains makes constraints visible to the user. While the LOEC visualization is not an "ecological interface display", it still supports the Gibsonian ecological approach that supports the principle of direct perception (Burns & Hajdukiewicz, 2004).

The colors on the LOEC visualization provide an aid to the user determining a path[1]. It is important to point out that the LOEC visualization alone does not identify the least-costly path for

[1] Specific instructions about LOEC visualization and its use for participants are found within each experiment description.

the user (does not show paths) but rather presents information about minimum total cost field changes across the entire problem space. For the case of path planning, the problem space is the terrain and environmental variables. Ideally, the human decision maker should make a path that follows a gradient descent, guided by the changes in color (from purple to yellow), from the start location to the goal (see also Figure 4.25). This means that every "step" in the path should be proportional to the negative of the gradient at a particular point. The "auto-path" function (see section 4.4) identifies the least-costly path in this manner (by following the least gradient descent).

For instance, the least costly path from the start to goal locations goes through a way-area (the orange polygon in Figure 4.26), and the human decision maker has the choice of specifically traversing through area "A" or "B". In order to reach the goal, it is inevitable to traverse through some areas that are purple, like the start in this example is in a slight purple zone. The human decision maker should attempt to follow the color gradient from purple to yellow. This is not the same as constantly following a yellow contour, as this could result in high path costs. The color in area "A" has more purple than the color in area "B". This communicates to the human decision maker that the minimum total cost from area "A" to the goal might be greater than that in area "B". In order to avoid higher path costs, creating a path that goes through area "B" as opposed to "A" would likely be more advantageous and less costly. The human decision maker would use this information alongside the other displays (e.g., path cost table and path elevation profiles) in order to compare path solutions. Thus, the LOEC visualization leverages direct perception, allowing path planners to perceptually understand constraints and path costs by visually representing the total cost field.

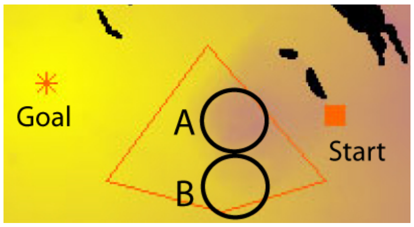

Figure 4.26 Example use of LOEC visualization for path planning

Finally, the LOEC visualization provides an aggregate view of the minimum total cost field, which was calculated using all the variables pertinent to the cost function. This may be particularly important for non-intuitive cost functions, such as those that rely on sun position as opposed to terrain information. Furthermore, the LOEC may guide sensitivity analysis as users will want to match path segments with corresponding LOEC colors. It is hypothesized that the LOEC visualization would be helpful for users in understanding the complete problem space because it integrates multiple variables and reduces a complex problem to one that is more intuitively and visually obvious.

4.8 OUTPUT FILES

For experimental purposes, once the user completes planning a path, and submits a path answer through the "Done" button, the path planner outputs two text files. The first text file is a summary of the paths submitted (and is the only file the first version of PATH outputs). The second text file is a complete listing of all the mouse-clicks the user has executed (tracking of interaction between user and interface).

The first basic text file includes the time spent making a path and the time modifying the path (in milliseconds), and the total path cost of all paths present when user ended path planning, including the waypoints of these. The second text file the following information: trial number, time stamp, mouse-click stamp code, path cost (if applicable), and path waypoints (if applicable). If a mouse-click is associated with a change in path cost (i.e., making and modifying paths), the path cost and waypoints are saved.

5 Experiment 1: Optimizing Sun-related Cost Functions

5.1 Experimental Objectives

The primary objective of this experiment was to better understand human-automation path planning, which included verification of selected metrics as an appropriate method for quantifying human optimization. The results of this experiment are aimed at addressing the advantages and disadvantages of higher amounts of data integration and automation, and their impact on human path planning performance. A secondary objective was to evaluate PATH as a path planning tool and to validate the experimental protocol for a larger study on a simpler test case. In addition, sun-related cost functions were the central focus as these were deemed to be atypical (i.e., people do not typically try to optimize sun position or geometrically dependent variables). These sun-related cost functions also had incremental number of variables between functions, a similar attribute to the other path-related cost functions to be tested in the follow-on experiment (e.g., distance, time, metabolic cost).

5.2 Experimental Methods

5.2.1 Equipment: PATH Interface

The decision support interface used was PATH (Figure 5.1), with which the participants were able to make, modify and submit the least-costly paths they had planned. The experiment was run using the a four screen computer workstation, three of which were utilized: one screen for the introduction materials, a second for PATH, and a third presented the situation awareness questions asked between trials (Figure 5.2). The computer screens have a 16-bit color resolution at 1280 x

1024 pixels, and the screen-capture program Camtasia® simultaneously ran on the computer in order to obtain archival video of the user interactions with PATH. The workstation was a Dell Optiplex GX280 with a Pentium 4 processor.

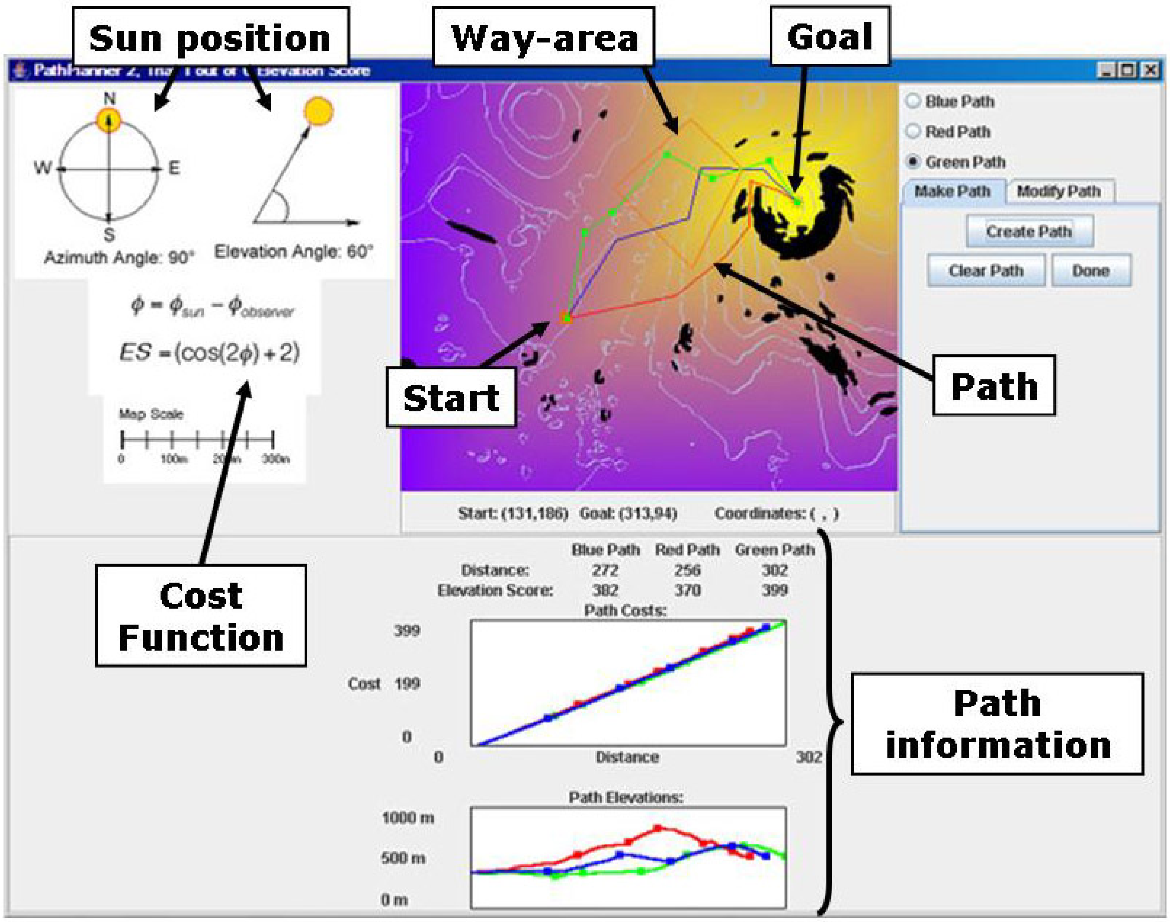

Figure 5.1 PATH interface for experiment 1, annotated

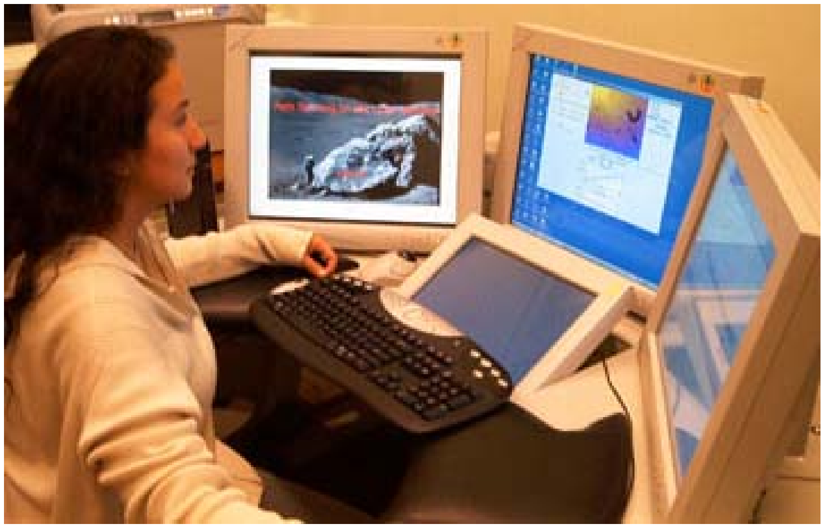

Figure 5.2 Experimental set-up

5.2.2 TASK

For this experiment, participants were asked to complete the following task: using the given computer interface, make an obstacle-free, least-costly path with at least one waypoint within the designated way-area. The cost for each path is based on a cost (or objective) function, pre-determined by the experimenter. Each trial has a given start and goal locations as well as a designated critical way-area. Least-costly paths for each trial always traverse the designated critical way-areas. These are on the lunar terrain map provided via PATH. Environmental conditions, i.e., sun azimuth and elevation angles, that were relevant to the optimized cost function were presented on the interface and changed for each trial (but not within trials). After planning a path, subjects submitted their path solution. After each trial, participants were asked a couple of situation awareness questions that directly related to the previous trial before continuing to the next. Subjects had to complete four path planning trials.

5.2.3 INDEPENDENT VARIABLES

Three independent variables were tested in this experiment: type of visualization (3 types depicted in Figure 5.4, elevation contours, levels of equal cost (LOEC), and combination of elevation contours and LOEC), level of automation (the 2 levels described previously, passive and active), and cost function (2 functions, Elevation Score, ES, and Sun Score, SS). While visualization type was a between-subject variable, cost functions and automation type were within-subject variables, resulting in a 2 x 2 x 3 repeated measures design (Figure 5.3).

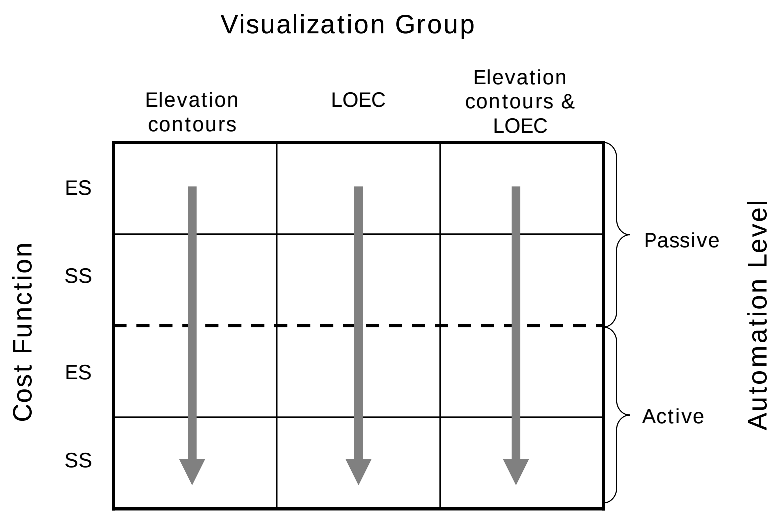

Figure 5.3 Summary of experimental conditions for experiment 1

Figure 5.4 Possible map visualizations, including start & goal locations and designated way-area. From left to right, (a) elevation contours visualization, (b) levels of equal cost visualization, and (c) both visualizations.

The independent variable of visualization was chosen as a between-subject condition because naïve participants were needed for the test trials[1]. Furthermore, this experimental design resulted in a reasonable time involvement per participant (about 1.5 hours). Thus, participants were randomly placed into one of three different visualization groups. The trials that were tested in the other two independent variables, cost function and automation type, were not randomized because a previous pilot study[2] showed that counterbalancing was not effective. It was determined that participants were going to exhibit a learning curve regardless of presentation order. Thus, the order of easiest to hardest was implemented in an attempt to equalize this learning effect. Additionally, from the pilot study, it appeared that using the active automation first would bias the passive path planning strategies. The first two trials used passive automation, and the last two, active automation. Within each automation type, participants first made an ES path and then an SS path. The selected presentation order for the cost function was consistent with the increase in difficulty of the functions. In summary, all participants were asked to complete four possible path planning trials (Table 5.1).

Table 5.1 Summary of trial order for experiment 1, optimizing sun-related cost functions

Passive automation trials		Active automation trials	
Elevation Score trial	Sun Score trial	Elevation Score trial	Sun Score trial
Trial 1	Trial 2	Trial 3	Trial 4

Participants were randomly distributed into one of three possible groups which were assigned to a map visualization: elevation contours visualization, levels of equal cost (LOEC) visualization, or both visualizations (Figure 5.4). This was the only difference between groups; all other elements, such as tables and modifying path functionalities, remained the same. The elevation contour map, which is the nominal map that users would expect, directly presented elevation gradients from which users could infer rates of change, but no other cost function information. With the LOEC visualization, participants were presented with an aggregate of information, terrain and costs. Since

[1] The same trials could not be shown between visualization group (if within-subjects variables) as this could possibly result in a confounding learning effect.

[2] See Appendix A for a summary of pilot study.

the LOEC visualization was likely not as familiar as the contour map, a third visualization map, the combination of LOEC and elevation contours, was also tested. This visualization could be powerful as it provides the participant with both the raw data and the total cost map.

Two increasingly complex cost functions were used: Elevation Score (ES) and Sun Score (SS), Figure 5.5. ES is considered a simpler function than SS as it has fewer variables to optimize. ES relates the sun's elevation angle to the observer's elevation angle, or terrain slope. SS not only encompasses the same information as the ES function, but also includes the relationship between sun's azimuth angle and the observer's azimuth angle, or direction of travel. The optimal sun angle is when the sun is high in the sky (approaching 90 degrees in relative latitude) and at a cross angle from the direction of travel (at 90/270 degrees in relative longitude). See 4.3.1 for more details.

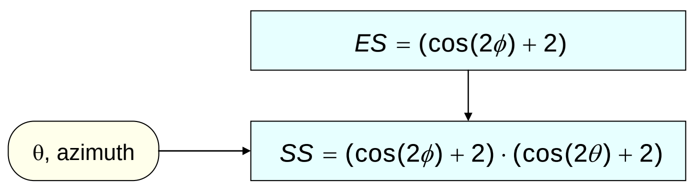

Figure 5.5 Flow and interdependence between cost functions for first experiment

Participants were tested on the two automation levels: passive and active automation. More specifically, in passive automation, the user created a path by selecting path waypoints that were connected by straight path segments. In active automation, the user only defined one waypoint, in the critical way-area, and then the automation calculated and plotted least-costly paths from the start to the waypoint and from the waypoint to the goal.

5.2.4 DEPENDENT VARIABLES

Path planning performance was measured by final path cost, total time to complete trial (both time spent making and modifying path), and the number of situation awareness (SA) questions that were answered correctly. Multiple choice questions were used as a global measure of the participants SA, which was expected to vary depending on automation levels. After every trial, participants were asked two questions about the previous trial. SA is (a) the perception of elements in the current environment, (b) the integration and comprehension of these elements, and (c) the projection of future status based on comprehension (Endsley, 1995), and the SA questions addressed the first two characteristics (Endsley, 1988). Specifically, participants were asked about the elements in the display (e.g., sun positions), and the cost functions (e.g., how path costs would be affected by changes in variables). There were a total of eight multiple-choice questions asked, four per automation level. SA questions can be found in Appendix A.

5.2.5 EXPERIMENTAL HYPOTHESES

The first experiment with PATH was designed to investigate how well participants performed in creating least-costly paths when interacting with the passive and active automation levels, as well as the different types of visualization, with increasingly difficult cost functions. It was hypothesized that with active automation, participants would be able to create near-optimal least-costly paths, regardless of the cost function, in a shorter period of time as compared to passive automation. However, it was hypothesized smaller errors and shorter times would be achieved at the expense of decreased situational awareness. Finally, it was hypothesized that within the passive automation level, the LOEC visualization would assist participants in creating least-costly paths and in shorter periods of time as compared to participants that did not have that visualization, especially for more difficult cost functions.

5.2.6 SUBJECT INSTRUCTIONS

After participants were assigned to one of three possible visualization groups, they completed a pre-questionnaire (see Appendix A) that asked about their average video game usage and their self-rating on map use experience. No color-blind participants completed the experiment.

There were two instructional phases in this experiment. In the first, participants were given an overview of the task and their designated visualization. The written explanation for each of the three possible visualizations can be found in Appendix A. They practiced the passive automation with two trials, one for each of the cost functions under investigation. There was one practice SA question given. After the training trials, participants completed the test trials; they had a five minute time limit on each trial. In the second phase, participants were instructed on how the active automation worked, and two practice trials preceded the active automation test trials.

As participants were conducting their path planning task, a video capture of the screen was taken. At the end of four trials, all subjects reviewed their video and described in detail their cognitive strategy used in making their optimal paths. All participants completed a post-questionnaire that asked them to rate the usefulness of elements within the computer interface.

5.2.7 PARTICIPANTS

Twenty-seven participants volunteered for this experiment, with an average age of 25.7 ± 3.6 years. Participants were primarily graduate students, with 18 men and 9 women, equally distributed between the three visualization groups. There was no significant difference in distribution between average video-game usage and their self-ratings on map use experience.

5.3 RESULTS

Analyses were conducted on the path costs percent errors, total time to task completion, percent time spent modifying path, and number of correctly answered situational awareness questions. An alpha level of 0.05 for all statistical tests was used. Analyses of variance were applied to analyze the data; if the assumptions for these tests were not met, non-parametric tests were used (Kruskal-Wallis test for between-subject variables and Wilcoxon Signed Rank test for within-subject variables).

5.3.1 PATH COST ERRORS

Path cost percent errors were calculated by comparing the path cost generated by the participant to the automation's minimum path cost. The range of these errors for each condition, visualization, automation type, and cost function is depicted in Figure 5.6. Using non-parametric tests, significant differences across automation type and cost function were found.

In general, participants were able to optimize paths to within 35% of the theoretical optimal least cost even when the cost functions were unfamiliar and had little automated decision support. When provided with automated decision support, participants were able to generate a path to within 2% of the optimal. For the ES cost function, a Wilcoxon Sign Rank test yielded a significant difference across automation type ($Z = -4.54$, $df = 1$, $p < 0.001$), resulting in smaller path cost percent errors for active automation (M = 0.24%, SD = 0.26) as compared to passive automation (M = 4.88%, SD = 0.96). Similarly for SS paths, the more difficult cost function, a Wilcoxon Sign Rank test (Z = -4.54, df = 1, p < 0.001) indicated that smaller errors were achieved when participants used active automation (M = 0.25%, SD = 0.17) as opposed to passive automation (M = 15.53%, SD = 6.30). This effect was consistent across each of the visualizations.

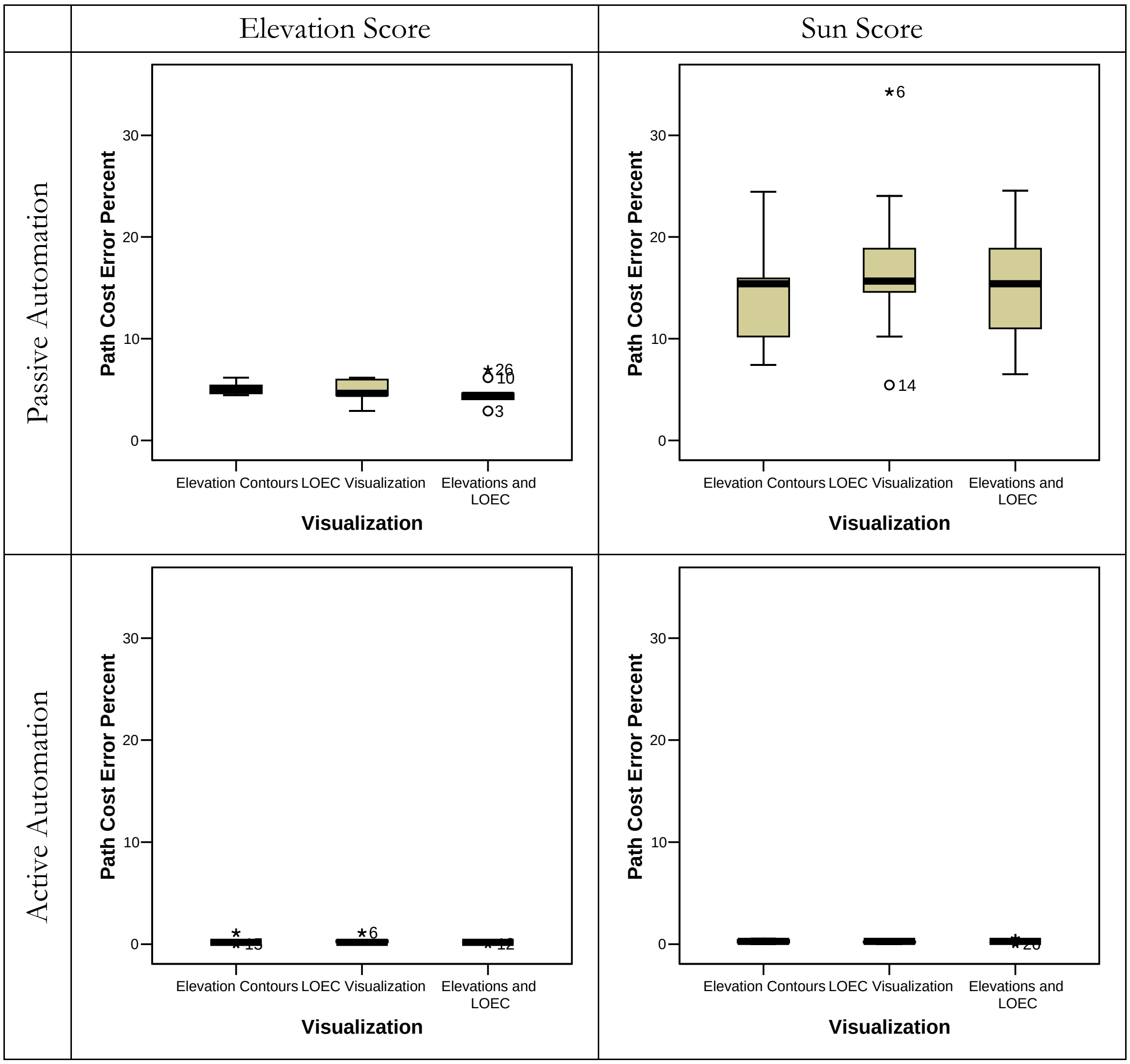

Figure 5.6 Box-plot of path cost errors between visualizations, automation levels, and cost functions

Differences across cost functions were investigated within each automation type. Within passive automation, a Wilcoxon Sign Rank test (Z = -4.52, df = 1, p < 0.001) showed that SS path errors (M = 15.53%, SD = 6.30) were significantly larger than ES path errors (M = 4.88%, SD = 0.96). This effect was consistent across each of the visualizations. Within active automation, there was no overall difference between the ES and SS path errors (Wilcoxon Sign Rank test, Z = -0.77, df = 1, p = 0.440). This effect was consistent for two of the three visualizations (elevation contours visualization and LOEC visualization). For the participants that had both visualizations (elevation contours and LOEC), there was a marginally significant difference across cost functions (Wilcoxon Sign Rank test, Z = -1.85, df = 1, p = 0.06): SS active path errors (M = 0.29%, SD = 0.17) were larger than ES active path errors (M = 0.16%, SD = 0.06).

A Kruskal-Wallis test was performed on each combination of cost function and automation type to examine the differences across visualizations. For each of the four conditions (i.e., trials), there was no significant difference between the visualizations (ES passive, χ^2 (2, N =27) = 1.87, p = 0.39; SS passive, χ^2 (2, N =27) = 0.42, p = 0.81 ; ES active, χ^2 (2, N =27) = 3.19, p = 0.20; SS active, χ^2 (2, N =27) = 1.27, p = 0.53).

Possible effects of gender, video usage, or map use experience were investigated. There was no effect of video usage and map use experience. When comparing if path cost errors differed between men and women participants, since the ratio was uneven (in this experiment it was 1:2), gender was not considered.

In summary, with respect to path cost percent error, the visualization had no main effect on the subjects' performance within ES or SS regardless of level of automation. Participants, in general, had smaller errors for ES paths than SS paths within passive automation. Overall, path cost errors were smallest within active automation, where there was no difference between the cost functions.

5.3.2 TOTAL TIME TO TASK COMPLETION

Figure 5.7 shows a box-plot of times to task completion (in seconds) across visualizations, automation type, and cost function. A repeated measures analysis of variance (2 x 2 x 3) was performed to investigate the differences in total time to task completion between all the conditions.

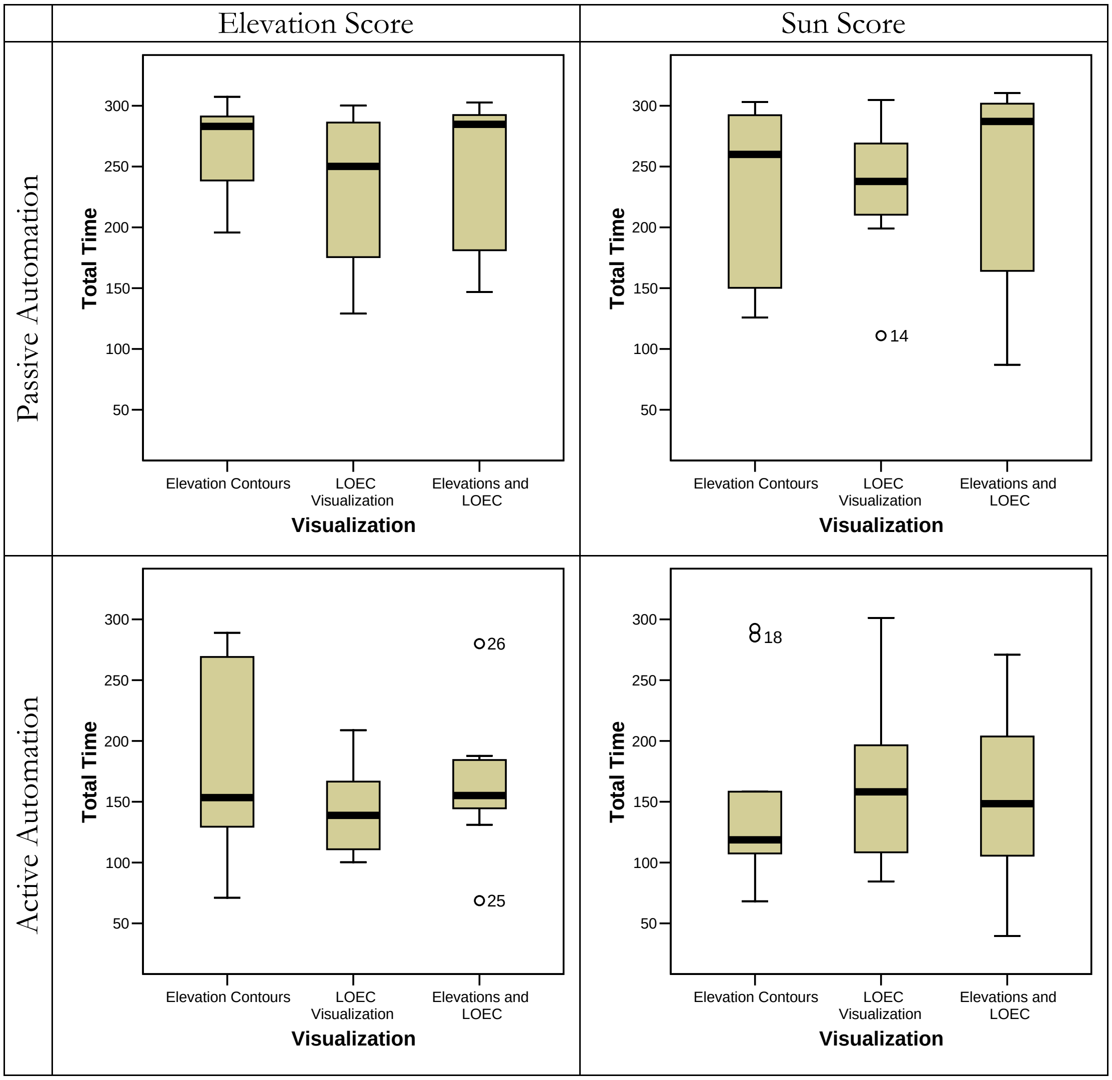

Figure 5.7 Box-plot of total time to task completion (seconds) across visualization, automation type, and cost function

There was no significant difference across visualizations with respect to total time ($F(2,24) = 0.10$, $p = 0.91$). Expectedly, participants took significantly less time to complete the task when using active automation ($M = 162.44$, $SD = 69.04$) than when using passive automation ($M = 241.87$, $SD = 63.77$) ($F(1,24) = 58.10$, $p < 0.001$). This difference is about 1.3 minutes on average.

A marginally significant difference was found across cost functions ($F(1,24) = 3.70$, $p = 0.07$) for completion time. On average, participants took slightly longer to make ES paths ($M = 207.79$, $SD = 71.82$) than SS paths ($M = 196.52$, $SD = 82.62$). However, there was a significant interaction between cost function and visualization (F(2,24) = 5.78, p = 0.009). As seen in Figure 5.8, the interaction was caused primarily by the active automation. It appears that LOEC helped participants arrive more quickly at a solution for the ES cost function. Participants that had elevation contours in their visualization took longer to make ES paths than SS paths, yet for participants with the LOEC visualization, the opposite trend is seen. Simple contrasts revealed no significant differences between cost functions within specific visualization groups.

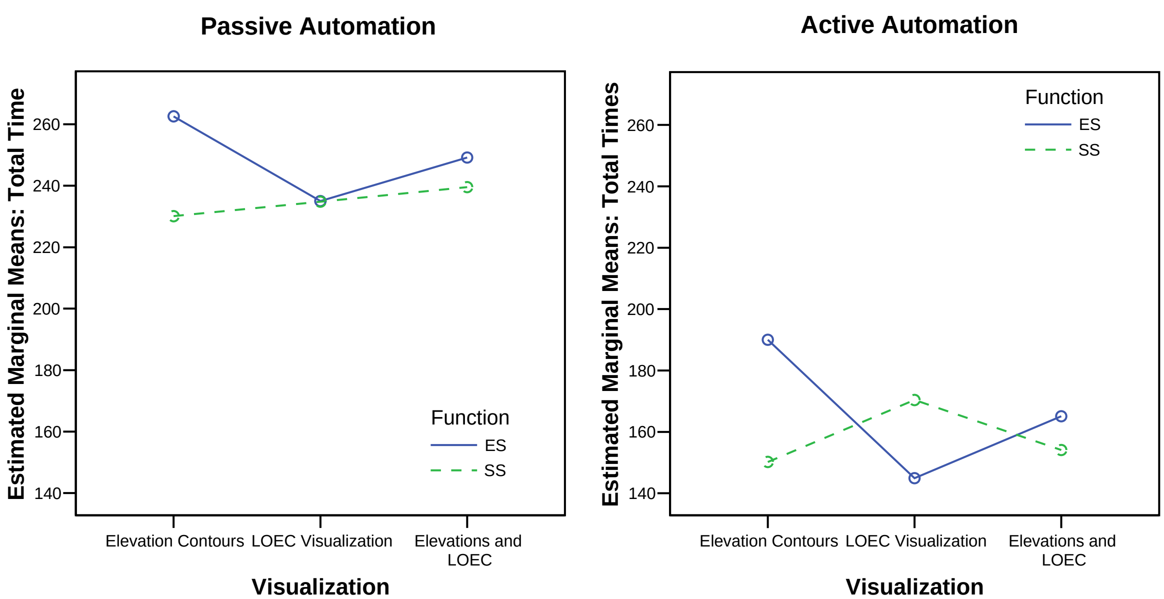

Figure 5.8 Means plot of total time across visualization and cost functions: passive automation (left) and active automation (right)

In summary, when using active automation, participants were able to significantly reduce the amount of total time spent completing the path planning task by about 1.3 minutes. Within the passive automation, most participants had the tendency to take most of their allotted time for the task. No main effect of visualization was detected. There was only a marginal significant difference across cost functions, where participants spent slightly longer times optimizing ES paths than SS paths, though there was a significant interaction between visualization and cost functions. It appears that LOEC subjects spent more time on SS paths than ES paths, while the subjects in the other two groups had the opposite effect.

5.3.3 Percent Time Spent Modifying Path

Participants, when creating a least-costly path with passive automation, spent a large portion of their time modifying paths by moving, adding, and deleting waypoints. Assessing how much time participants devoted to a sensitivity analysis on their path solution will provides insight in understanding how humans conduct optimization. Most participants did not use this functionality with the active automation as much, choosing instead to repeatedly make new paths (see Figure 5.9). There are two possible reasons for this trend. First, participants may have found modifying a path was more time consuming than just making a new path with the active automation; second, participants likely thought they could only make paths less optimal by modifying them as the active automation plotted least-costly paths between two waypoints. In order to further investigate this trend, the analysis was restricted to just the passive automation, where path modification was the most predominate.

Within the passive automation conditions, a 2 x 3 repeated measures analysis of variance (Figure 5.10) showed that there was a significant difference between cost functions ($F(1,24) = 7.25$, $p = 0.01$). Participants spent more of their time modifying the more difficult SS paths ($M = 50.13\%$, $SD = 25.24$) than the ES paths ($M = 41.85\%$, $SD = 24.25$). There was no main effect based on visualization ($F(2,24) = 1.35$, $p = 0.28$)) and no interaction was found between function and visualization ($F(2,24) = 0.54$, $p = 0.59$). Hence, participants proportionally spent more time modifying SS paths than ES paths in the passive automation phase of the experiment, regardless of which visualization was used.

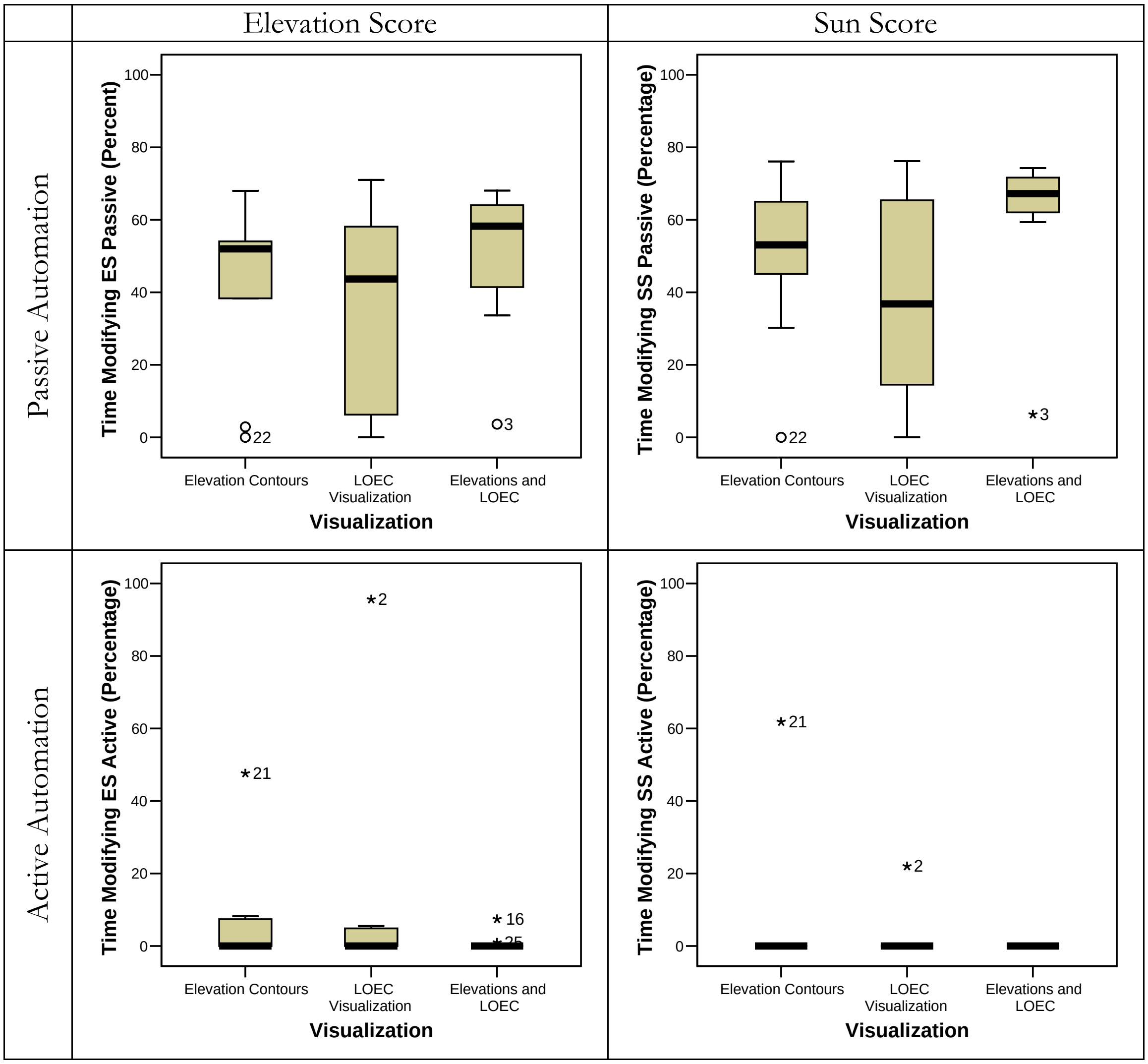

Figure 5.9 Box-plot of percent time spent modifying path across visualization, automation type, and cost function

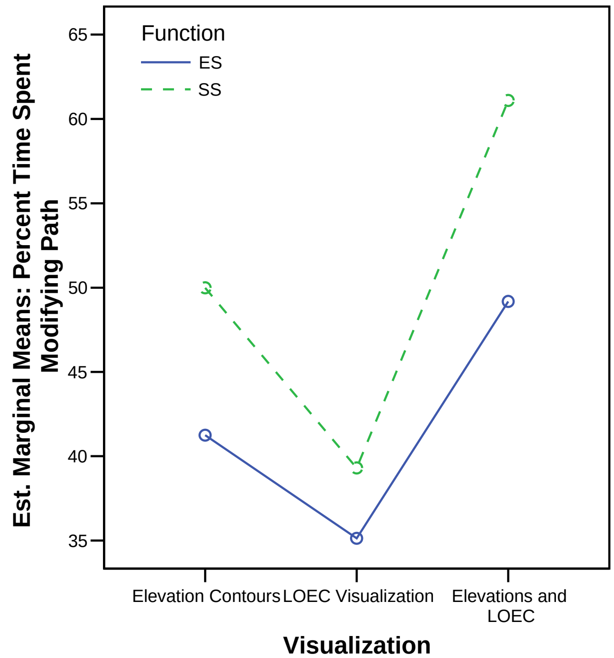

Figure 5.10 Means plot of percent time spent modifying path within passive automation across visualization and cost function

5.3.4 SITUATION AWARENESS

After each trial, two situational awareness (SA) questions were asked, totaling four questions for passive automation and four for active automation per participant. The distribution of correctly answered questions (regardless of visualization) is shown in Figure 5.11. Within active automation, there was one subject that answered no questions correctly and one subject with all correct answers. This distribution appears to be different as compared to the passive automation trials – where 12 subjects answered all four questions correctly and all subjects answered at least one question correctly. A non-parametric test (Wilcoxon Signed Rank test) was performed to determine a significant difference across automation type ($Z = -3.35$, df = 1, $p = 0.001$); participants answered less questions correctly during the active automation phase ($M = 2.33$, $SD = 0.78$) than during the passive automation phase ($M = 3.19$, $SD = 0.92$) of the experiment. No difference in SA was found between visualization groups (Kruskal-Wallis tests, within passive automation χ^2 (2, N = 27) = 1.72, $p = 0.42$; within active automation χ^2 (2, N =27) = 0.68, $p = 0.71$).

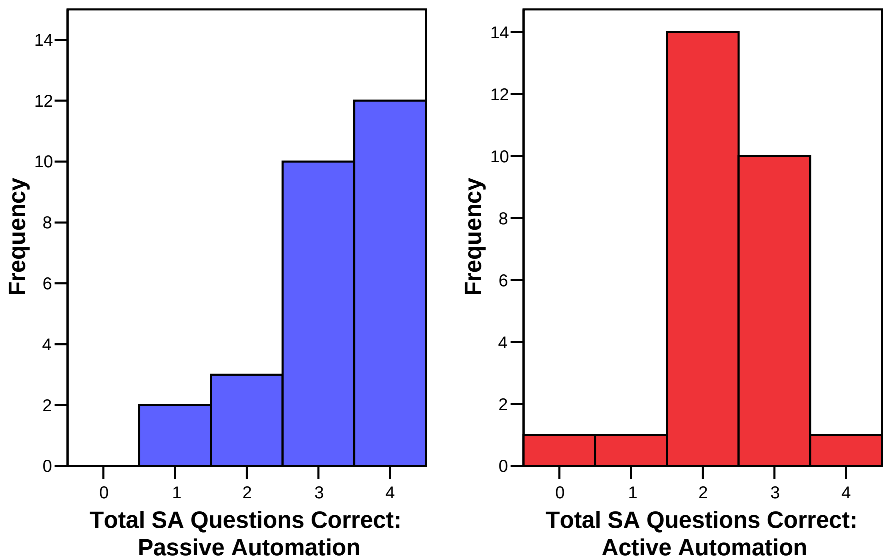

Figure 5.11 Distribution of correctly answered situation awareness questions for passive automation (left) and active automation (right)

5.4 COGNITIVE STRATEGIES

Based on experimental results, observations, and participant debriefs, two general path planning strategies were exhibited. In one strategy, participants made one or two paths and then spent the rest of their time modified paths, moving, adding and deleting waypoints (manual sensitivity analysis strategy). In the other strategy, participants made multiple paths, rarely utilizing the modifying path functionalities. These strategies were split between passive and active automation. During active automation, all participants tended not to manually modify their paths, choosing instead to make multiple paths in order to determine least-costly paths.

During passive automation, the most frequent strategy implemented was the manual sensitivity analysis, though some chose to make multiple paths. This division was apparent by assessing the distribution of average percent time spent modifying for passive trials (Figure 5.12), where those participants with an average greater than 40% applied the manual sensitivity analysis strategy. The selection of strategy was not based on visualization as there was no difference in distribution

(Pearson's chi-square test, $\chi^2(2,27) = 2.70$, $p = 0.26$). Furthermore, there was no difference in performance (based on path cost errors) between the strategies (Mann-Whitney tests, within ES, $Z = -0.39$, $p = 0.70$; within SS, $Z = -0.42$, $p = 0.68$).

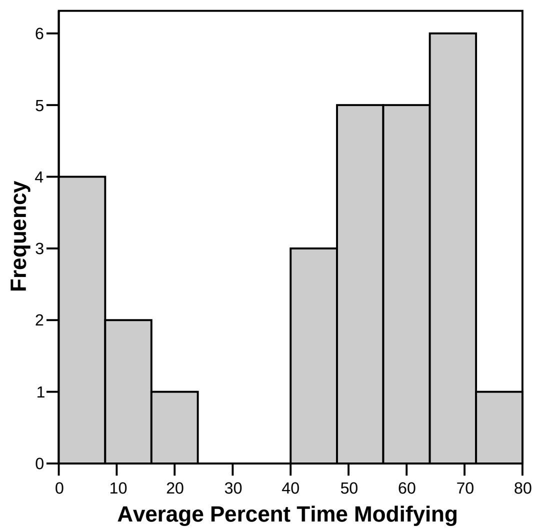

Figure 5.12 Histogram of average percent time spent modifying across passive trials

Participants who chose to make multiple paths before selecting their path solution did a type of "whole-path" sensitivity analysis. This was most evident in the active automation where it was observed that participants created multiple paths in order to explore the problem space. In this automation architecture, the participant had to only define one waypoint within the critical way-area and the automation generated the least-costly path segments. Participants defined many different waypoints, examining how path cost changed relative to where the waypoint was placed, essentially conducting a sensitivity analysis within the way-area. Thus, all participants implemented a type of sensitivity analysis, either manual or "whole-path", in order to optimize their path solutions.

5.5 DISCUSSION

In this experiment, there were three visualization groups, one with elevation contours, one with the levels of equal cost (LOEC), and one with both elevation contours and LOEC. In order to ensure that the participants in each visualization group were relatively the same, participants were randomly assigned to a visualization, balanced by gender and number (i.e., number of participant per group).

Furthermore, there was no statistical evidence that there was a group differences with respect to participants' map-use experience or choice of sensitivity analysis type. Thus, the participants within the visualization groups were reasonably balanced.

It was hypothesized that having the LOEC visualization would help participants make superior least-costly paths, resulting in smaller cost errors and shorter task times than participants who did not have the LOEC, particularly when trying to optimize the path cost whose cost function was more complex. The preceding analysis did not demonstrate a main effect due to type of visualization for any dependent variable (either path cost error, total times, or situation awareness).

There are several possible reasons why no effect based on the type of visualization was found. Some participants commented that they had not used the LOEC as a primary tool to make their least-costly path, citing reasons such as they did not know exactly how to use it. Another possibility is that the LOEC visualization is not particularly useful for cost functions with few variables. The Elevation Score (ES) only optimizes one variable and the Sun Score (SS) contained two variables. These functions might not be complex enough to merit the use of LOEC. Finally, more training time and an increased participant pool could have impacted the results.

The cost function factor produced a significant effect for the three dependent variables which is expected since they represent increasing problem complexity. For path costs within passive automation, ES path cost errors were significantly smaller than SS path cost errors, regardless of visualization. Within active automation, no overall difference between cost functions was found, but there was a marginally significant difference that favored ES paths for the visualization that had both LOEC and elevation contours. Thus, active automation decreased the task complexity with respect to minimizing path cost.

In terms of time to completion, the cost function factor had a marginally significant main effect, however, there was a significant interaction between cost function and visualization. It was expected participants would spend more time optimizing the more difficult function, SS, regardless of visualization and automation type. It appears, though, that with the direct presentation of elevation (i.e., the visualizations with elevation contours), subjects tended to tweak their solution for the purely, elevation-dependent cost function (i.e., ES) more than subjects who just had the LOEC visualization. Thus, the participants that had the elevation contours in their visualization spent more time on the simpler ES function. This is supported by the slightly lower percent time spent modifying for LOEC visualization group (compared to the other 2 visualization groups) for the ES cost function. These results indicate that the visualization shifts the manner in which subject chooses to conduct their sensitivity analysis. In essence, if the information is provided to the subjects, they will use it, though not necessarily to their advantage. In this case, the additional information of elevation contours on top of LOEC visualization gave the subject two factors to tweak their solution; this introduced a slightly larger error margin between cost functions in active automation and subjects in this visualization group appeared to spend more of their time modifying paths than the other two groups.

While the different visualizations did not significantly affect subject performance, the degree of automation dramatically affected performance across a number of dependent variables. As hypothesized, when subjects used the active automation, they made smaller path cost errors and took less time than when using the passive automation, regardless of visualization and type of cost function. The smaller path cost errors is not a surprising result as the automation is assisting the subjects in making the least-costly paths in a large, complex problem space. When using active automation, path cost errors were, at most, only a few percentages over the least possible cost, allowing subjects to drop about 1.3 minutes from solution times as compared to passive automation. For time critical tasks, this difference could be essential.

However, this improved performance in terms of solution time came at the cost of decreased situation awareness. In the passive automation trials, 81% of the subjects were able to answer 3 or more of the 4 SA questions, while during active automation, only 41% of subjects performed equally as well. This is likely because subjects spent less time at the task and did not conduct the same level of sensitivity analyses (as measured by the percent time spent modifying) as they did during passive automation. While the passive automation caused longer solution times, it also ensured that subjects became familiar with the problem and thus had a better understanding of the problem space than did those subjects who used the automation to plan the routes.

Moreover, it was clear that the two different automation levels produced two different planning strategies, which in turn likely affected their situation awareness. Participants did explore the problem space within active automation, as supported by the very small path cost errors, but they did so differently. They chose to make new paths instead of modifying paths, thus eliminating the "manual" sensitivity analysis. This strategy saved them time, but lowered their overall situation awareness. They paid less attention to elements on the PATH interface, not comprehending how the automation was calculating the least-costly path. When subjects had to do most of the problem solving in the path planning task (i.e., within passive automation), they appeared to conduct a more thorough sensitivity analysis when confronted with multi-variable cost functions and both LOEC and elevation contours. Unfortunately, while having the LOEC might have induced subjects to apply more sensitivity analysis, a strategy that might have preserved their situation awareness, the ease and quickness of using the active automation prevailed. Situation awareness thus appears to be a function of both time and sensitivity analysis for the geospatial task of path planning.

5.6 CONCLUSIONS FOR EXPERIMENT 1

In this experiment, two increasing degrees of automation, three different visualizations, and the interaction with optimizing increasingly complex cost functions were examined. No main visualization effect was found but the effect of the level of automation was strong and consistent across all dependent variables. After establishing such an effect in this experiment, the next experiment addresses if different visualizations can affect performance within a single automation decision support architecture.

When the automation generated most of the path for the participants, they were able to perform better in terms of time and path costs, but paid the price of decreased situation awareness. Having the levels of equal cost visualization promoted sensitivity analysis, but not within active automation, thus it was not enough to counter the loss of situation awareness. While the effects of automation level are striking and suggest that the best decision support aid would be one that is highly automated, the situation awareness measures demonstrate a significant drawback of highly automated systems in the reduction of SA. Similar automation biases, i.e., excessive reliance on computer-generated solutions, have been observed in other domains, such as critical event diagnosis and time-sensitive resource allocation (Cummings, 2004). These results indicate that the active automation essentially leveled the task difficulty across problem complexity. Consequentially participants did not look for more information than was necessary. Such automation bias is undesirable in time-critical domains because it increases likelihood of errors of omission and commission (Mosier & Skitka, 1996). Furthermore, the decision maker is less likely to perform well under unexpected situations with decreased situation awareness, preventing them from identifying situations in which the automation is not properly functioning and hindering them in knowledge-based reasoning that is necessary under these circumstances.

6 EXPERIMENT 2: HUMAN PATH OPTIMIZATION

6.1 EXPERIMENTAL OBJECTIVES

The objectives of this second experiment were to further evaluating human-automation path planning performance with the different visualizations and more complex conditions. The results of the first experiment (Chapter 5) led to focusing on only one automation decision support architecture: passive automation. The active automation in the first experiment led to superior performance with respect to path cost errors and total time, but no main effect due to visualization was detected. Additionally, in the first experiment the cost functions were relatively simple (1 – 2 variables), thus the visualization effect may be more significant with more complex cost functions, which will be tested in this experiment. Therefore, having established the effect of active automation, passive automation is only tested in order to further examine visualization effect.

The first experiment also determined that situation awareness decreased with the use of active automation, which was evidence of automation bias. Situation awareness is most invaluable when reacting to the unexpected. Under these circumstances, the path planner needs to take into account the discrepancies between the expected and what is actually happening. Discrepancies are inevitable as path planning (before the EVA mission) will rely on terrain information that may be incomplete or have limited resolution. All predictions will be based on this terrain information, and hence, map resolution and accuracy will be a primary driver for why underlying exploration cost models will be incorrect. For example, the planner may predict the astronaut should have 50% of oxygen remaining, but in reality, there is only 40%. Thus the astronaut is faced with using a decision aid which is based on exploration models that are erroneous or incomplete (typically called automation "brittleness"). The likelihood of this occurring is greatest in the early stages of exploration, when astronauts are still acquiring higher fidelity terrain and cost models. For this reason, in this second experiment, a degraded automation condition is tested.

6.2 EXPERIMENTAL METHODS

6.2.1 EQUIPMENT: PATH INTERFACE

The decision support interface used was PATH (version 2, Figure 6.1), with which the participants were able to make, modify and submit least-costly paths. The experiment was conducted using the Multi-Modal Watch Station, using the same system set up as in the first experiment (see 5.2.1), with the exception that only two screens were used: one for introductory materials and the second for PATH.

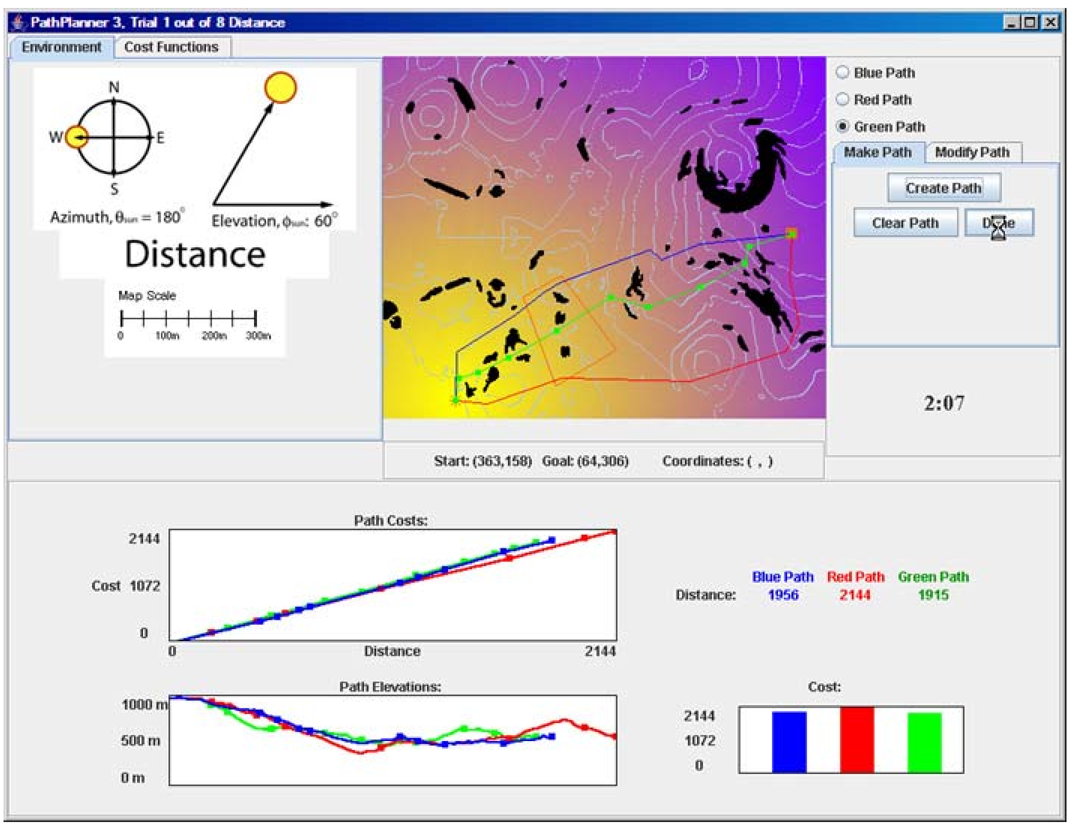

Figure 6.1 PATH, version 2, used in Experiment 2

The PATH interface version used for this experiment included a modified terrain map of Cone Crater, a timer clock, and user interaction tracking, which resulted in an additional output file that included every mouse-click the participant did during each trial along with tracking the time and cost of every path made. Also, slight modifications on the interface were made, such as the bar graphs (lower right corner of Figure 6.1) and the model of the cost functions under a new tab (left top corner). The new tab was added for two reasons: 1) to describe all the cost functions in one location, and 2) to allow for tracking of participants' attempts to access this information (as they had to click on the tab to view the cost functions).

6.2.2 TASK

As in the first experiment, participants were asked to make an obstacle-free, least-costly path (with at least one waypoint within the designated way-area) as fast as possible. The cost of each path was based on a cost function, pre-determined by the experimenter. Each trial had a given start and goal locations, a designated critical way-area, the sun's position for that trial, and lunar terrain map. Least-costly paths for each trial always traversed the critical way-area. After planning and optimizing a path, participants submitted their path solution. Participants had to complete a total of 6 test trials.

6.2.3 INDEPENDENT VARIABLES

Three independent variables were tested in this experiment, but under two experimental matrices (Figure 6.2). Within one matrix, the variables were type of visualization (3 types shown in Figure 6.3) and cost function (4 functions, discussed below). Within the second matrix, the variables were type of visualization (3 types), cost function (only 2 selected), and type of scenario (nominal and off-nominal). The off-nominal scenario represented a degraded automation condition. Since only a subset of the nominal cost functions were tested in the off-nominal case, two experimental matrices were required for the analysis and statistical models. While the visualization type was a between-subjects variable, the cost function and scenario type were within-subjects variables. Thus, there was a 3 x 4 repeated measures design for the first experimental matrix, and a 2 x 2 x 3 repeated measures design for the second matrix (Figure 6.2).

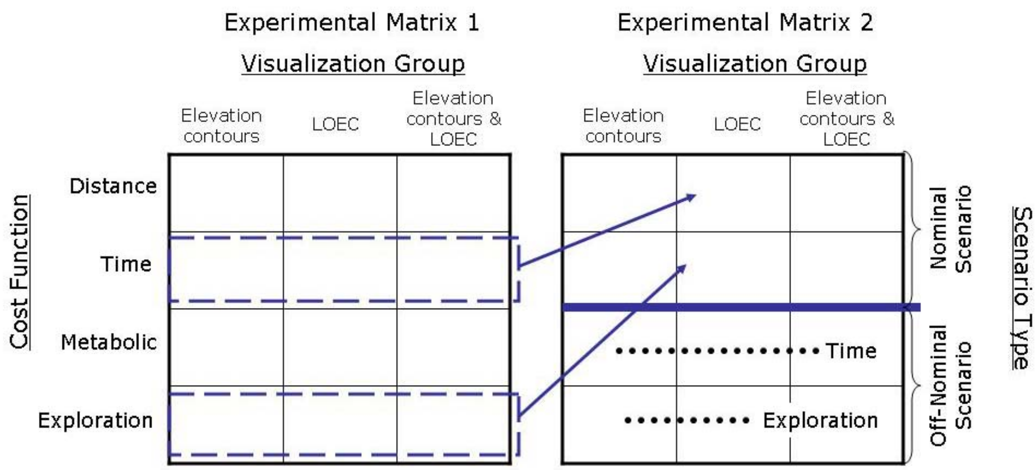

Figure 6.2 Experimental conditions and matrices for second experiment

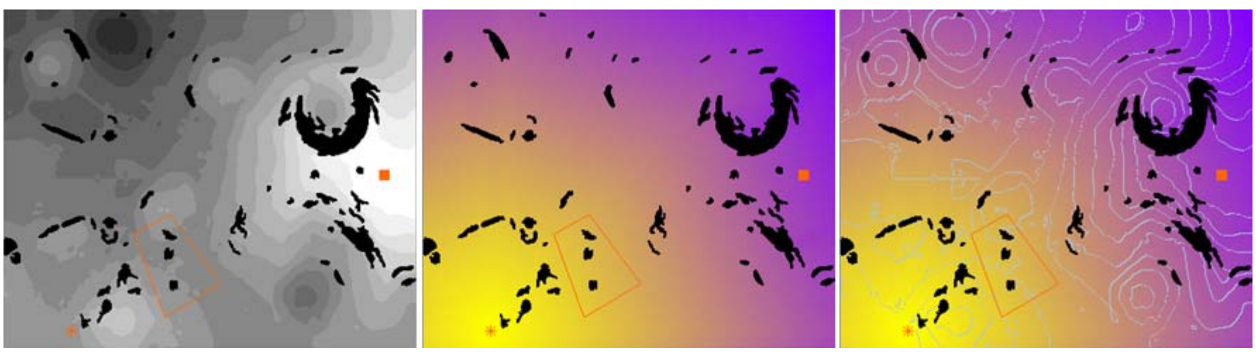

Figure 6.3 Possible map visualizations, including start & goal locations and designated way-area. From left to right, (a) elevation contours visualization, (b) LOEC visualization, and (c) both visualizations

As in the first experiment, participants were randomly distributed into one of three possible visualization groups: elevation contours visualization, levels of equal cost (LOEC) visualization, or both visualizations (Figure 6.3). While the visualization was different between participants, all other PATH features remained constant, such as the path information displays and the ability to modify paths.

The same three visualizations were tested for similar reasons presented in the first experiment. As all but one cost function depended on slope (and thus, elevation) information, the elevation contours remained the nominal map users would expect. The LOEC visualization (aggregate cost information) was automatically generated based on the cost function models. The third visualization, which presented both LOEC and elevation contours, combined the total cost map and the raw elevation data.

Four increasingly complex cost functions were tested in this experiment: Distance, Time, Metabolic, and Exploration (see section 4.3 for detailed explanations of cost functions). The first cost function was the shortest distance between two points, i.e., Distance cost function. The Time cost function depended on Distance and slope, as astronaut velocity relied on slope. The Metabolic cost function built upon the Time function, including slope and velocity, to determine energy consumed as a function of terrain. Finally, the Exploration function combined Metabolic costs and Sun Score as an overall cost function. Sun Score, a quantifiable measure of favorable lighting condition, related the sun's position (azimuth and elevation angles) with the observer's direction of travel. This cost function was tested in the first experiment. Thus, the Exploration cost function was the most complex function as it captured the costs that were fundamentally related to Distance and Time as well as spatial information (relative sun position). See Figure 6.4 for summary of cost functions, depicting interdependence and increasing complexity of the tested functions.

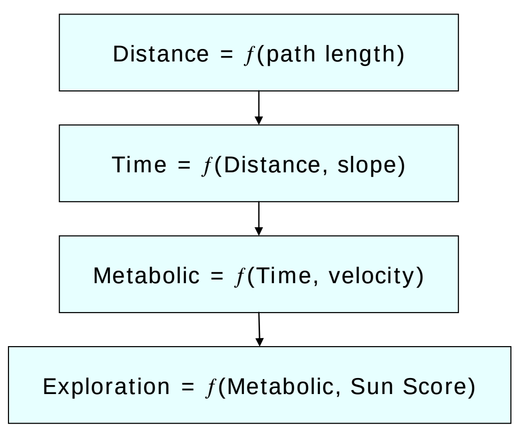

Figure 6.4 Flow and interdependences between cost functions for second experiment

Participants were tested in all four cost functions under nominal scenarios and only two cost functions under off-nominal scenarios (totaling 6 test trials). In the nominal scenario, participants were told they could rely on the PATH interface to provide them with accurate path cost based on the four previously discussed cost functions. In the off-nominal scenario, participants were informed that PATH's cost function models were inaccurate. This is the additional degraded automation condition. Under the off-nominal scenario, participants were only asked to optimize two cost functions: Time and Exploration. These two were selected for the off-nominal case as they represented a simple and a complex function (two versus four variables).

Even though all participants were asked to complete six possible path planning trials, they only were presented with four sets of start and goal locations (Table 6.1). In the off-nominal trials, participants repeated the start and goal locations experienced in the Time and Exploration trials, but the maps were rotated (Figure 6.5) in order to disguise the fact that the same trial was presented again. This, in addition to not informing the participants that the off-nominal trials were repeated, was done to prevent a learning effect across scenarios but to also ensure a comparable level of scenario difficulty. As in the first experiment, the order of the cost functions was not randomized among participants but rather was presented in order of increasing number of variables manipulated (in increasing difficulty). Participants completed the nominal trials first and then the off-nominal. The rationale for these experimental design choices is similar as in the first experiment.

Table 6.1 Summary of trial order for experiment 2, optimizing path planning cost functions

Nominal scenario				Off-nominal scenario	
Distance trial	Time trial	Metabolic trial	Exploration trial	Time trial	Exploration trial
Trial 1	Trial 2	Trial 3	Trial 4	Trial 2 (repeat)	Trial 4 (repeat)

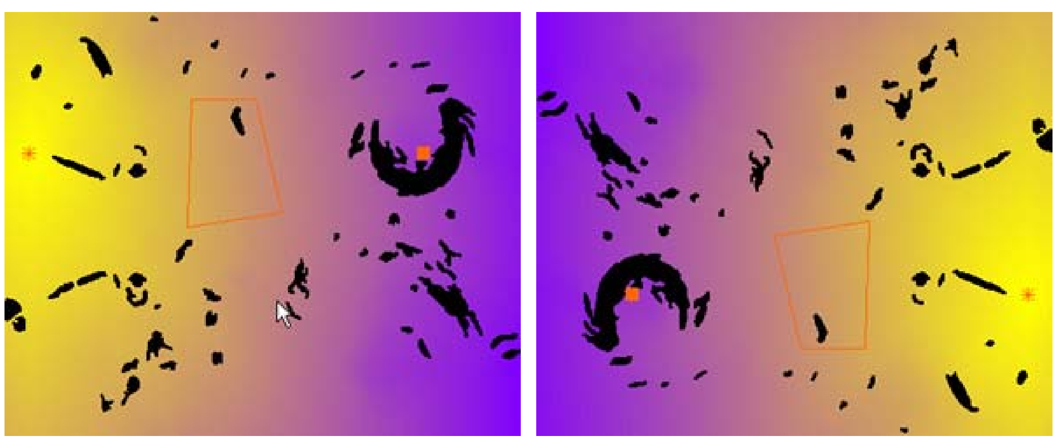

Figure 6.5 Terrain map example comparison between nominal (left) and off-nominal (right) scenarios (with LOEC visualization)

6.2.4 DEPENDENT VARIABLES

Path planning performance was measured by final path cost, total time to complete trial (both time spent making and modifying path), and path cost profiles. A path cost profile (example, Figure 6.6) is the cost of every path the participant made over the time they completed the trial. From the path cost profiles, a few other dependent measures were identified: true time, differential cost, and non-optimal satisficing (i.e., percent time spent conducting non-optimizing satisficing and the corresponding cost surplus).

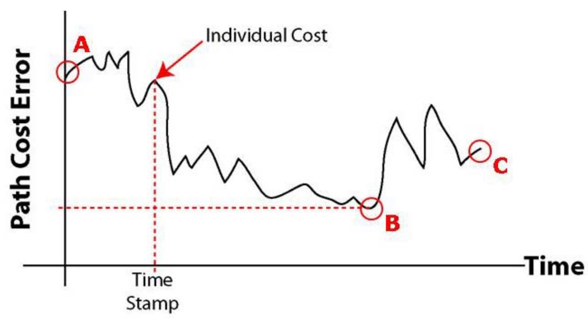

Figure 6.6 Path cost profile illustration

Figure 6.6 illustrates the different measures generated from the path cost profiles. Point A is the cost for the first path created, while point C is the submitted path cost with its corresponding total time; point B is the actual minimum path cost found with its matching time. True time is the time in which the participant actually found their minimum cost path (the time at point B in Figure 6.6). Differential cost is the difference between the submitted path cost and the first path cost made (path cost error disparity between point A and C in Figure 6.6). Finally, non-optimizing satisficing is defined as any additional time after a minimum path cost was achieved, where participants were unsuccessful in finding a lower path cost solution. Non-optimizing satisficing includes both time and cost errors between the minimum path cost achieved and the submitted costs. In Figure 6.6, this corresponds to the path cost error and the time differences between point B and C.

With respect to total time to complete task, it was converted to time penalty. Participants were asked to complete the task as well and as fast as possible. The time pressure was imposed by showing the participant a timer, an incremental clock. The penalty time started after 4 minutes (τ,

tau), which was not told to the participants. In a pilot study with an equivalent task, when participants were not told to take time into consideration, the 75^{th} percentile of total time to completion was ~ 4 minutes. Thus, this was deemed an appropriate time limit, as most participants would be able to complete the task while providing some time pressure.

6.2.5 EXPERIMENTAL HYPOTHESES

This second experiment was planned to examine how well participants performed in creating least-costly paths when interacting with PATH, across different visualizations, within only the passive automation architecture. Furthermore, performance and strategy changes were of interest under nominal and off-nominal conditions, as well as between the increasingly difficult cost functions. It was hypothesized that performance would deteriorate as the number of variables manipulated within the cost functions increased. However, because the problem space was made perceptually salient, participants with the levels of equal cost visualization (LOEC) should not experience the same path planning performance decline as those with no multivariate visualization. Degraded performance would be indicated by an increase in path cost error, total time, and true time. Furthermore, it was hypothesized performance would decrease in the off-nominal scenarios. However, participants with the visualizations that contained elevation contours would be able to optimize their paths better than the participants that just had the levels of equal cost visualization. Participants with just the LOEC visualization would be too dependent on their erroneous visualization (a form of automation bias) and lacked the elevation contours that would assist them in conducting the optimization with degraded cost models.

6.2.6 SUBJECT INSTRUCTIONS

Participants were randomly assigned to one of three possible visualization groups. Participant from the previous experiment were excluded from this one. Each filled out a pre-questionnaire that asked about average video game use and their self-rating on map use experience. The rating (Table 6.2) was changed from the first experiment to be more specific on map use experience. No color-blind participants completed the experiment. All participants were also given a "map planning" test which is suggested to measure "speed in visually exploring a wide or complicated spatial field" (Ekstrom, French, & Harman, 1979, pg. 39). This test was selected because it required participants to find the shortest path from one point to another in a map maze and hence, might be a measure of the participants' path planning ability.

Table 6.2 Map use experience self-rating descriptors

Ranking	Map use experience description
0	I have not done much hiking and am not familiar with using topographical maps.
1	I am familiar with topographical maps, but have not used them to plan or during hiking trips.
2	I have done hiking trip but I am not very familiar with topographical maps, in particular, using them during hiking trips.
3	I have planned and done hiking trips with the use of a topographical map.
4	I have planned and done many hiking trips with the use of a topographical map. I have used the map to navigate terrain beyond trials and/or to triangulate my position during the excursion.

There were two instructional phases in this experiment. In the first, participants were given detailed instructions about the task, the time pressure, the cost functions that were to be optimized, and the visualization they were assigned. They were given a practice trial before every nominal test trial for each cost function, i.e., practice trial preceded every test trial. Participants were instructed that they had to minimize the path cost as fast as possible; they were informed that there was a slight advantage in doing the task in less time but larger penalties for longer times.

If LOEC was part of a participant's visualization, the cost map was explained. Because of previous subjective feedback indicating confusion over the LOEC visualization in the first experiment, a more in-depth explanation of the LOEC visualization was included in the introduction. Written description of each visualization can be found in Appendix B.

In the second phase, participants were told that within the PATH planner "something is wrong with the cost functions." They were given two graphs (Figure 6.7) to review and examine which showed the differences between the expected costs (under nominal scenario) and the observed costs (under off-nominal scenario). The graphs were presented to the participants so that they could acquire a notional idea as to how the cost function models were erroneous. This was designed to be analogous to a real-world situation, where automation inaccuracies were noticeable but could not be immediately addressed. For example, an astronaut might note that actual oxygen readings were not what were predicted by the path planner.

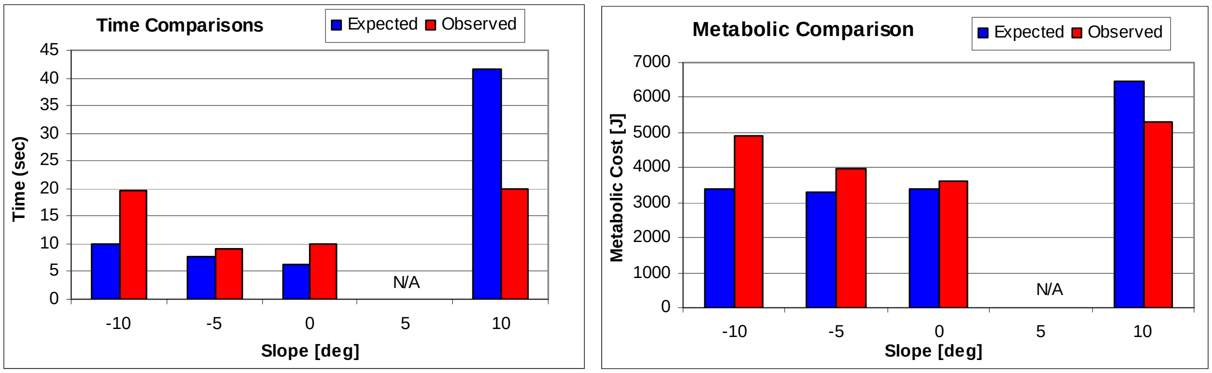

Figure 6.7 Deviations of cost functions between nominal and off-nominal scenarios, instruction comparative graphs

A video capture of the screen was taken as participants interacted with the path planning tool. At the end of the trials, all participants reviewed their video and discussed strategies used to optimize path. Finally, a post-questionnaire was administered that asked participants to rate the usefulness of elements of PATH. The same questions from the first experiment were asked except for an additional usefulness rating for the new bar graphs and the preference question (for only the participants that had both LOEC and elevation contours visualizations) was modified to ask if participants agreed with the statement: "I preferred the elevation contours over the LOEC visualization to make least-costly paths."

6.2.7 PARTICIPANTS

Thirty-four participants volunteered for this experiment, and were compensated ($10/hour) for their participation. Their average age was 25.0 ± 3.5 years. Participants were primarily graduate students, with 22 men and 12 women, equally distributed between the visualization groups. There was no significant difference in distribution between average video-game usage, map planning test score, and their self-ratings on map use & hiking experience.

6.3 RESULTS

Analyses of variance were used to test hypotheses if assumptions were met. Otherwise appropriate non-parametric tests were used. An alpha level of 0.05 for all statistical tests was applied. As two experimental matrices were tested, the results are divided into Phase 1 (3 x 4 nominal cases) and Phase 2 (2 x 2 x 3 scenario comparisons with the off-nominal condition). No covariates were used in the subsequent analysis. Neither map planning scores nor map & hiking experience were significantly correlated with path cost errors and time penalty.

For detailed test results and descriptive statistics, refer to Appendix B.

6.3.1 PATH COST ERRORS

Path cost errors were calculated by normalizing the path cost generated by each participant to the automation's minimum path cost. Non-parametric tests were used to examine the differences across conditions.

6.3.1.1 PHASE 1

The range of path cost errors[1] for phase 1 of the experiment are shown in Figure 6.8. Within each cost function, there was no statistical difference between visualization groups. As Figure 6.8 suggests, there was a significant difference between cost functions (Friedman test, $p < 0.001$). Wilcoxon Sign tests confirmed the following ranking: the Time cost function (M = 1.60, SD = 0.14) had significantly larger path cost errors ($p < 0.0001$), Distance had the smallest (M = 1.03, SD = 0.03), and there was no statistical difference between Metabolic (M = 1.07, SD = 0.02) and Exploration (M = 1.06, SD = 0.02) cost functions. Within visualizations, the results were similar (in agreement with the lack of visualization differences).

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[1] Two data points were identified as outliers (3.44*SD and 4.28*SD above the mean) and were removed. If data greater than 3.29*SD, as recommended by Tabachnick and Fidell (2001), it was considered an outlier.

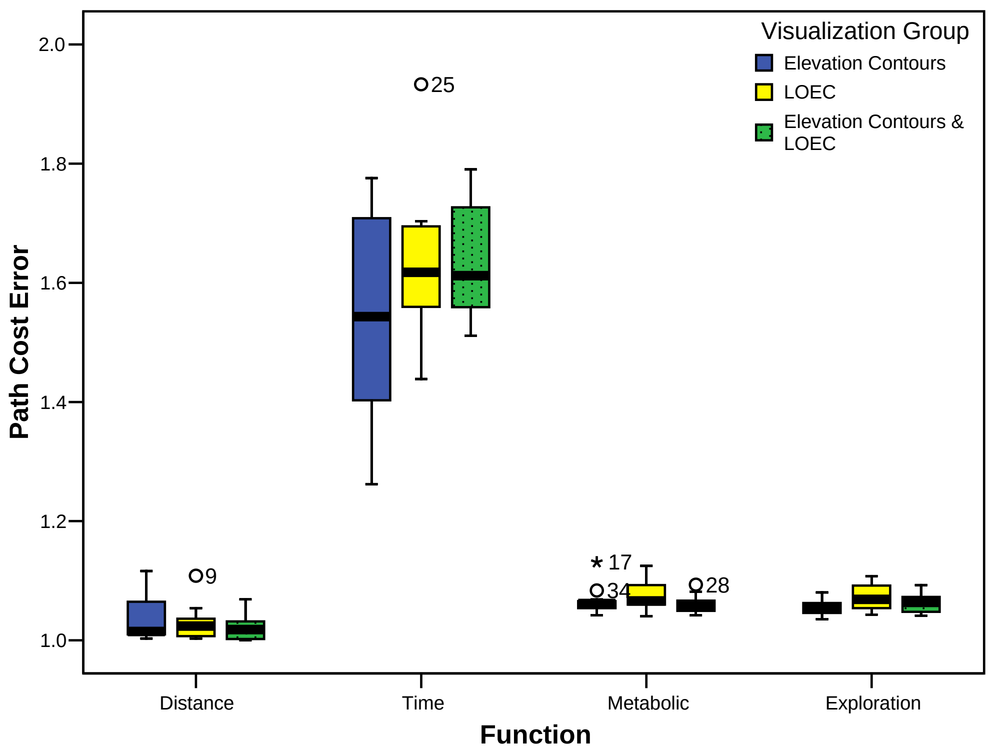

Figure 6.8 Box-plot of path cost errors between visualizations and cost functions, Phase 1

6.3.1.2 PHASE 2

The range of path cost errors for the second phase of this experiment is shown Figure 6.9. Using Kruskal-Wallis tests, no significant differences in path cost errors across visualizations were found within the Time nor the Exploration off-nominal trials. This is consistent with the nominal scenario, which indicates that visualizations did not affect path cost errors. Similar to the nominal scenario, the off-nominal Time path cost errors (M = 1.53, SD = 0.20) were significantly higher ($p <$ 0.0001) than the off-nominal Exploration path cost errors (M = 1.10, SD =0.03).

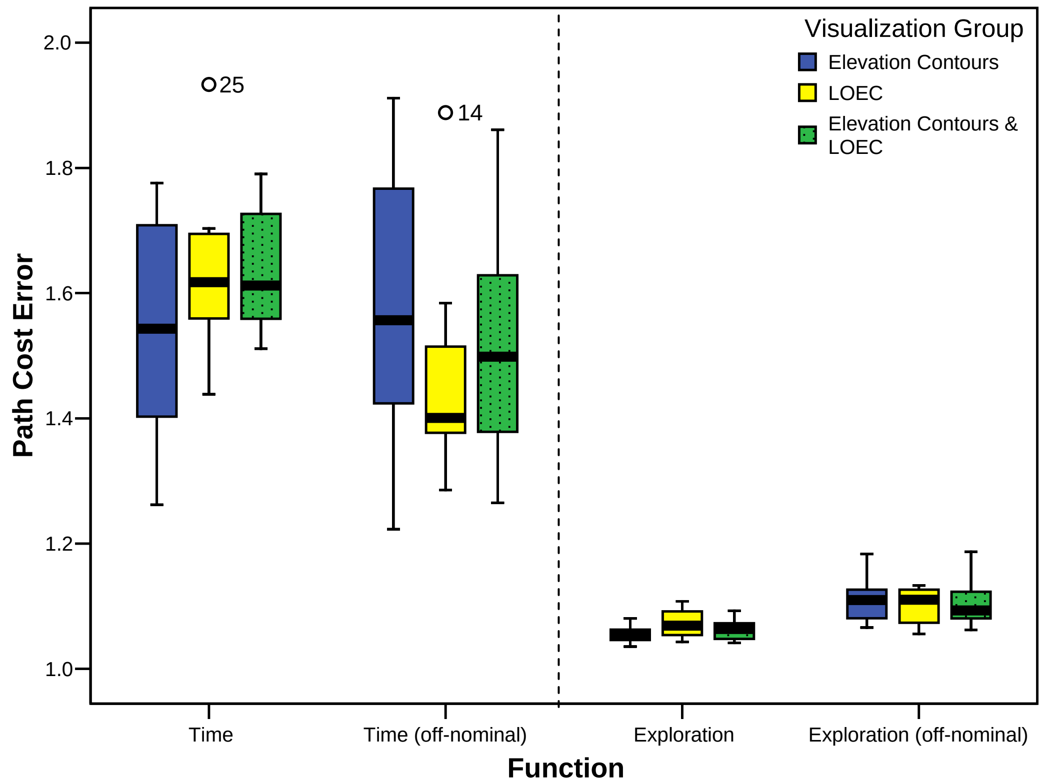

Figure 6.9 Box-plot of path cost errors between visualizations and scenario type, Phase 2

Wilcoxon Sign tests were used to compare across scenarios (nominal vs. off-nominal cost functions). Overall, regardless of visualization, there was a significant difference in path cost errors between scenarios. The path cost errors for the nominal Time cost function were significantly larger than the off-nominal errors ($p = 0.05$). The opposite effect was found for the Exploration cost function, where the path cost errors were significantly lower in the nominal scenario ($p < 0.0001$).

Further comparisons between nominal and off-nominal scenarios were conducted within each visualization group. For the Exploration cost function, participants within each visualization group had a significantly lower path cost errors for the nominal than the off-nominal scenario. For the Time cost function, the difference across scenarios was driven by the significant decrease in off-nominal path cost errors for the LOEC participants ($p = 0.026$). No significant differences across scenarios were detected for the other two visualization groups. These results suggest that only the participants with the LOEC visualization decreased their path cost errors for the Time off-nominal trial.

In summary, within the off-nominal scenario, visualization did not have a main effect on overall path cost errors, and the Time cost function resulted in larger errors than the Exploration function, which is consistent with the nominal scenario results. Across scenarios, the results were mixed. Within Time, errors decreased during the off-nominal scenario, though it was mainly due to the performance of the LOEC participants. Within Exploration, errors increased during the off-nominal scenario consistently across all visualization groups.

6.3.2 TOTAL TIME: TIME PENALTY

Total time to complete the task was transformed to time penalty ($e^{t/\tau}$; t, total time, τ, 4 minutes). Time penalty was used, as opposed to total time, because participants were instructed that there was a penalty for spending too much time on the task, i.e., they were to optimize the path as fast as possible. As the time penalty is an exponential transformation, the median Levene's test (Brown & Forsythe, 1974) was used to test for equal variance. Repeated measures analyses of variance were performed to investigate differences between the conditions. If the sphericity assumption[1] was not met, the Greenhouse-Geisser adjusted p-value is reported.

6.3.2.1 PHASE 1

A box-plot of the time penalties across visualizations and cost functions[2] is shown in Figure 6.10. A repeated ANOVA (3 x 4, visualization x cost function, Figure 6.11) revealed a significant difference between cost functions ($p = 0.001$) but no significant difference across visualizations nor interaction between treatments.

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[1] The sphericity assumption is similar to the ANOVA requirement of homogeneity of variances, except that it is within-subjects. The assumption is that variances of the differences (between pairs) across groups are the same.

[2] One outlier (4.14*SD above the mean) was removed.

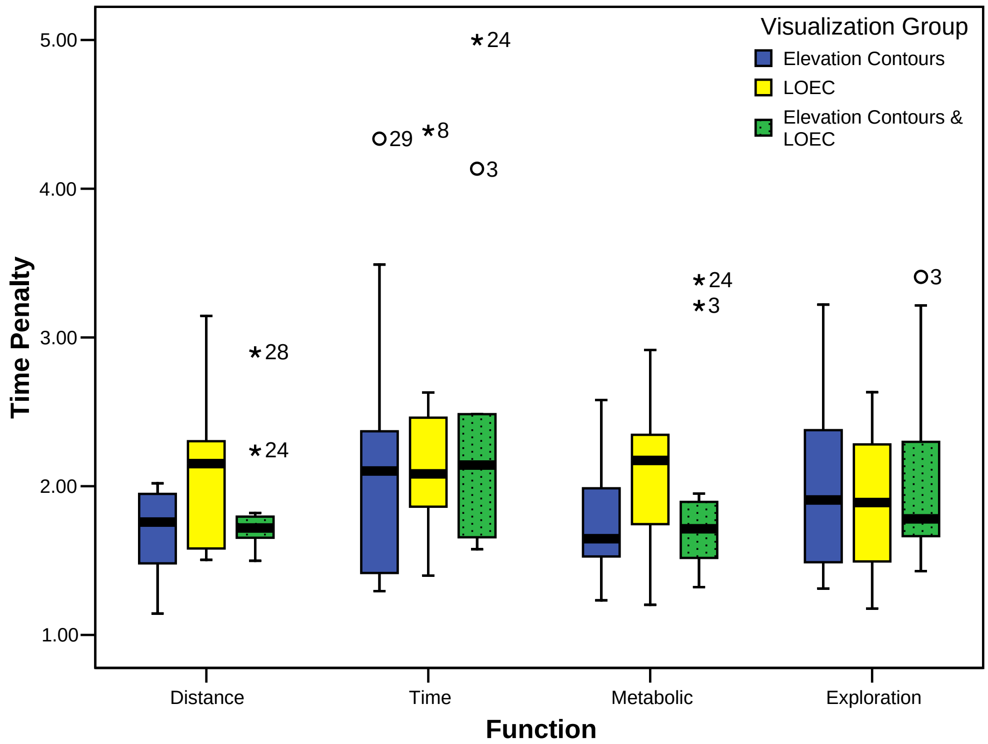

Figure 6.10 Box-plot of time penalty between visualization and cost functions, Phase 1

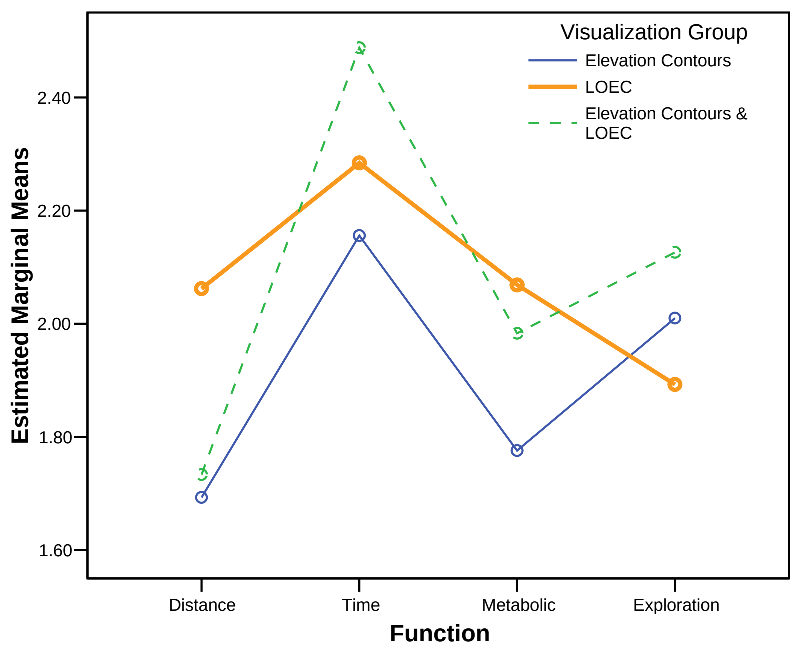

Figure 6.11 Means plot of time penalty across visualization and cost functions, Phase 1

In order to determine which cost functions affected the participants the most, all pair-wise comparisons were conducted (Bonferroni test). The Time cost function took the longest to optimize as the time penalties were significantly larger than the ones for Distance ($p = 0.003$), Metabolic ($p < 0.0001$) and Exploration cost functions ($p = 0.007$). There were no other significant differences between the other functions (i.e., equal time spent in Distance, Metabolic, and Exploration trials).

Even though there was no difference detected across visualizations, Figure 6.11 shows an interesting trend for the LOEC visualization group. The two groups that had elevation contours in the visualization had an increase in time penalty for the Time and Exploration cost functions only. On the other hand, participants that had just the LOEC visualization did not have an increase for Exploration function, but rather a slight decrease. Additionally, for this visualization group, there does not appear to be much of a difference across the cost functions as there is with the other two groups. In order to understand if and how the LOEC visualization affected the time penalties (and thus the total time spent on the task), further investigation was conducted within this visualization. A simple main effects analysis of cost function within the LOEC visualization group showed that there were no significant differences between functions. The results imply that the LOEC visualization participants spent relatively equal amounts of time optimizing each cost function.

In summary, the Time cost function took the longest time to optimize, resulting in the highest time penalty. No other significant differences between cost function were detected. While no main effect due to visualization was detected using ANOVA, the trend within the LOEC group showed that these participants spent relatively equal amounts of time for each cost function.

6.3.2.2 PHASE 2

A repeated ANOVA (2 x 2 x 3, scenario x cost function x visualization) was implemented to detect differences among the conditions. Figure 6.12 shows the range of time penalties for the conditions tested[1]. There was only a significant difference with respect to cost function ($p < 0.0001$). There

[1] Two outliers (4.14*SD and 3.51*SD above the mean) were removed.

were no significant differences between visualization groups or scenarios, and no significant interactions between the conditions were detected. This implies that the scenario did not affect the time spent in trying to optimize paths, and only the cost function caused a change in total time penalty. In this case, participants spent more time optimizing the Time cost function than the Exploration cost function (Figure 6.13).

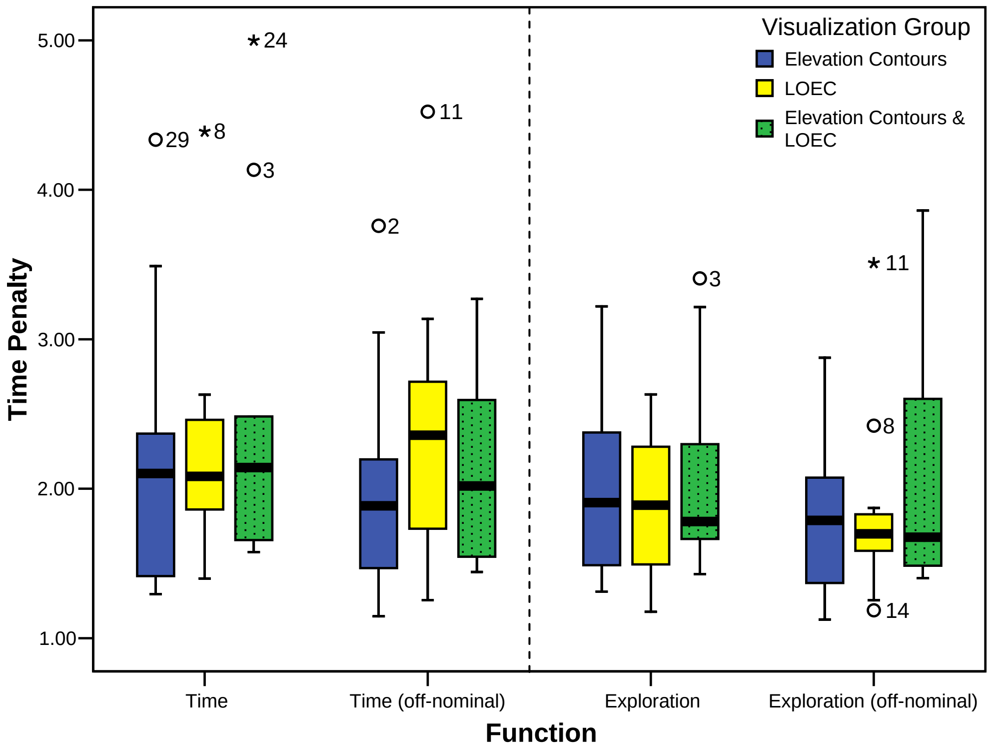

Figure 6.12 Box-plot of time penalties between visualizations and scenario type, Phase 2

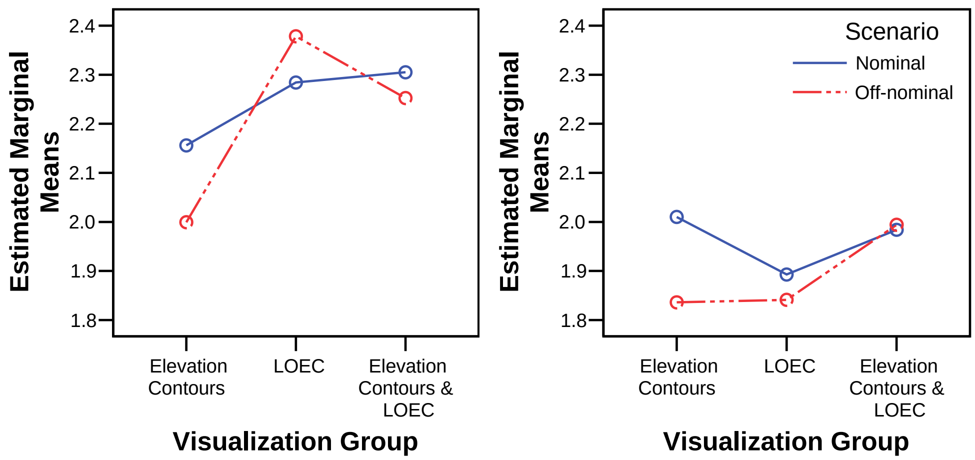

Figure 6.13 Means plot of time penalty across visualization, type of scenario, and cost function (Time, left; Exploration, right)

6.3.3 PERCENT TIME SPENT MODIFYING PATH

Percent time spent modifying paths was calculated as the ratio between time modifying to total time. This is an important measure because it is an indicator of the amount of sensitivity analysis conducted during path optimization.

6.3.3.1 PHASE 1

Figure 6.14 shows the box-plot of the percent time spent modifying. A repeated measures ANOVA showed there was no overall difference across functions or visualization group, and no significant interaction between treatments was detected. While there was no significant difference between conditions, Figure 6.15 suggests a trend based on visualization, which merits further investigation. The trend appears to be that when the LOEC was present in the visualization, participants were inclined to spend more of their time modifying paths than participants who just had the elevation contours.

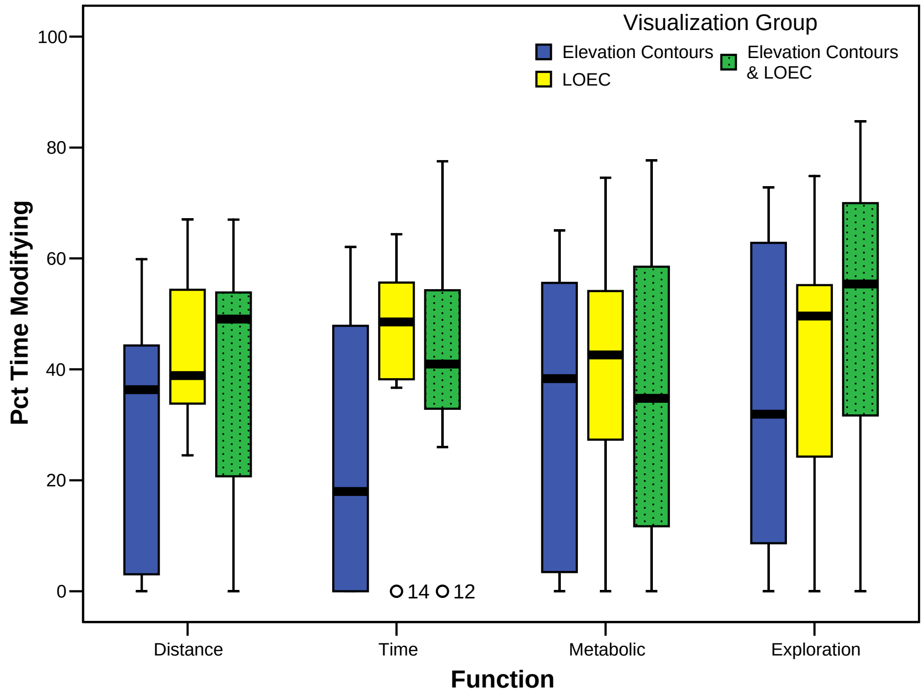

Figure 6.14 Box-plot of percent time spent modifying path between visualization and cost function, Phase 1

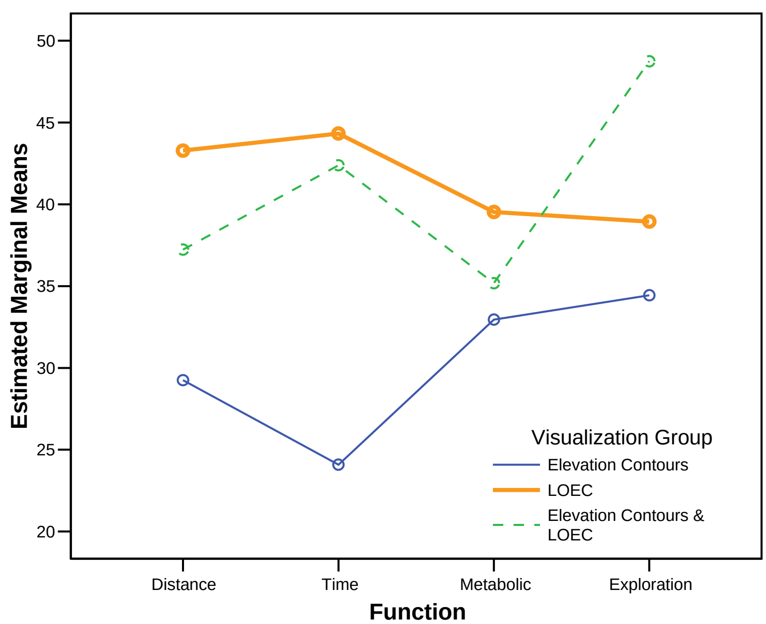

Figure 6.15 Means plot of percent time spent modifying path between visualizations and cost functions, Phase 1

Since the trend appears to be LOEC participants were spending more modifying time, all participants were re-grouped into two groups, those with LOEC and those without. While no significant main effect based on LOEC was detected, there was a significant difference across groups within the Time cost function only ($p = 0.016$). This implies that for the Time function, participants with LOEC in their visualization spent more of their time modifying paths (M = 43.36%, SD = 18.55) than those that did not (M = 24.09%, SD = 25.10). This effect was not seen with the other cost functions (Distance, Metabolic, nor Exploration). Therefore, the LOEC groups trend observed in Figure 6.15 is mostly due to the difference in percent time spent modifying only within the Time cost function.

From Figure 6.15, it also appears that within each visualization, cost functions do not seem to be treated equally, mainly for the groups that had elevation contours in their visualization. A simple main effects due to cost function within each visualization group did not reveal any significant differences. However, there was a significant increase of percent time spent modifying the Exploration cost function within the participants that had the elevation contours visualization. Within the elevation contours visualization group, point-wise comparisons showed that these participants had significantly higher percent modifying times for Metabolic and Exploration cost functions as compared to the Time function. Participants with the visualization group with both LOEC and elevation contours spent significantly higher percent modifying times for Exploration than Metabolic[1]. Thus, for these participants, the Exploration function was viewed as challenging, requiring more modifying time. Additionally, this difference within visualization supports the previous analysis in which indicated that participants who only had the elevation contours visualization spent less of their time modifying the Time cost function path.

In summary, there was no main effect between visualization groups and cost functions with respect to percent time spent modifying paths. However, there are some trends based on visualization. Only within the Time cost function were there any significant differences between visualizations: participants that had the LOEC visualization tended to spend more of their time conducting

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[1] Point-wise comparisons for Exploration cost function between each of the three visualization groups, did not reveal any differences.

sensitivity analysis on their paths as compared to those that did not have this visualization. Participants with just the elevation contours visualization tended to spend more of their time modifying paths with the Metabolic and Exploration cost functions than the Time function.

6.3.3.2 PHASE 2

Box-plots of the percent time spent modifying in the second phase of the experiment are shown in Figure 6.16. A repeated measure analysis of variance (2 x 2 x 3, scenario x cost function x visualization, Figure 6.17) was used to investigate the differences among the percent time spent modifying paths. There was no main effect of cost function, scenario, or visualization group. There were no significant interactions except for the interaction between cost function and visualization group ($p = 0.026$).

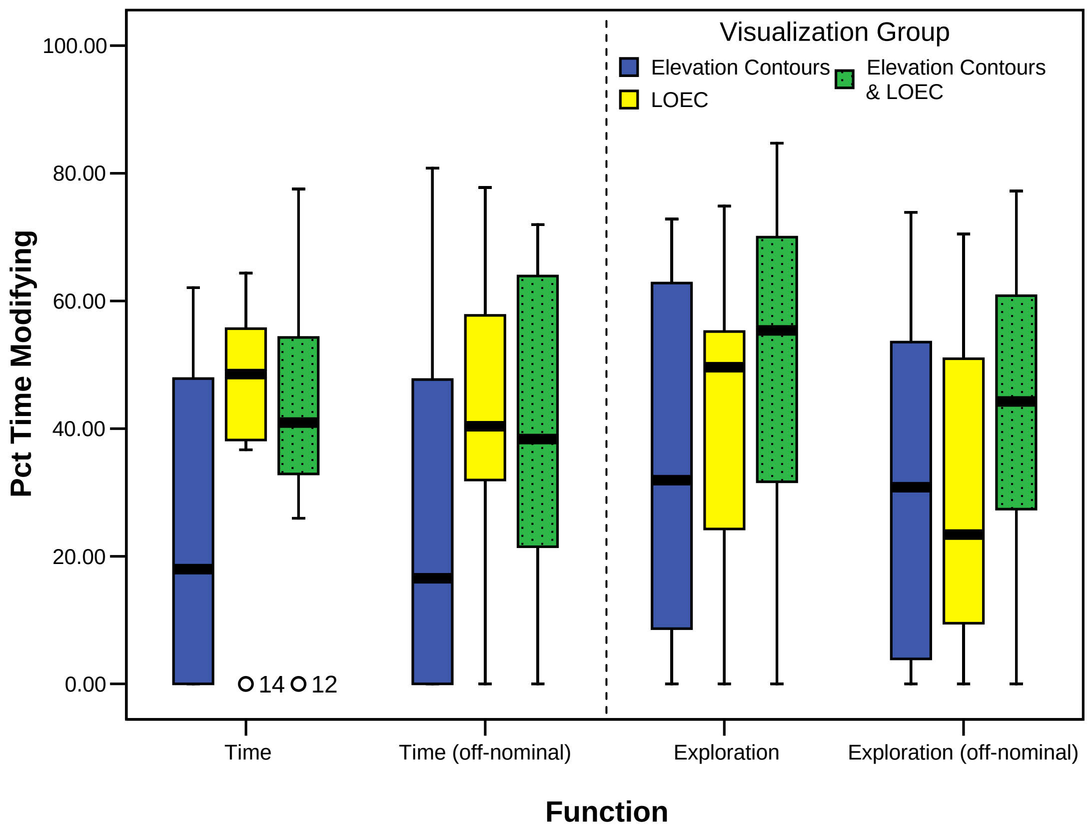

Figure 6.16 Box-plot of percent time spent modifying paths between visualizations and scenario type, Phase 2

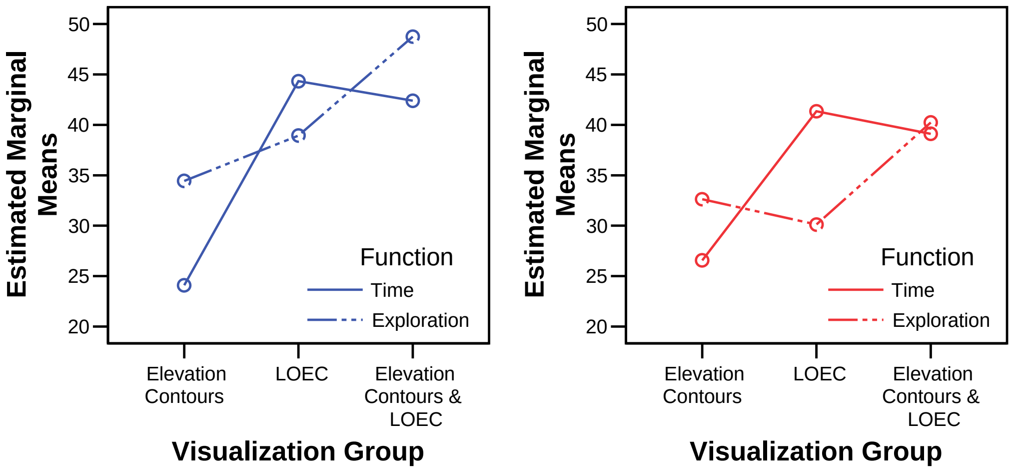

Figure 6.17 Means plot of percent time spent modifying across visualization, cost function, and scenario type (nominal, left; off-nominal, right)

The significant interaction deserves further analysis. The estimated means plot (Figure 6.17) seems to reveal a change in strategy between cost functions that depends on the visualization group. A simple effect analysis of function within visualization revealed that there was a marginally significant difference between functions within elevation contours visualization ($p = 0.054$) and a marginally significant difference within LOEC visualization ($p = 0.061$)[1]. Therefore, the detected significant interaction between cost function and visualization occurs because the participants within the elevation contours visualization spent a larger percent time modifying the Exploration cost function than the Time function while the participants within the LOEC visualization did the opposite, spending a larger percent time modifying the Time cost function than the Exploration.

In summary, no main effect was found between scenarios, cost function, nor visualization for percent time spent modifying. Of particular interest is the lack of difference across scenarios, as it was expected that degraded automation would prompt participants to conduct more sensitivity analysis as the path costs presented by the interface could not be trusted. There was a significant interaction between function and visualization, in which the elevation contours participants spent more time modifying Exploration paths than Time, while the LOEC participants tended to act in

[1] There was no significant difference to report for the third visualization group.

the opposite fashion. This was the same effect found in Phase 1, though it was more pronounced with the addition of the off-nominal scenario. The participants that had both visualizations spent equal amount of their time modifying both types of functions, regardless of scenario.

6.3.4 TRUE TIME

True time is a dependent measure that was derived from the path cost profiles (all path costs through the entirety of a single trial). True time is how long a participant took to arrive to the minimum path cost found. It differs from total time or time penalty because it reflects the actual time that it took a participant to optimize a path, excluding any time spent afterwards attempting to find another solution. Short true times indicate that participants were able to optimize the path quickly.

6.3.4.1 PHASE 1

Figure 6.18 shows the range of true times between visualizations and cost functions. A repeated measures ANOVA (3 x 4, visualization x cost function, Figure 6.19) only revealed a significant difference between cost functions ($p < 0.0001$). There were no significant differences across visualization and no significant interaction between treatments. It appears from Figure 6.19 that the Time cost function had the longest true time. Simple contrasts confirmed that Time cost function had significantly longer true times than any of the other cost functions.

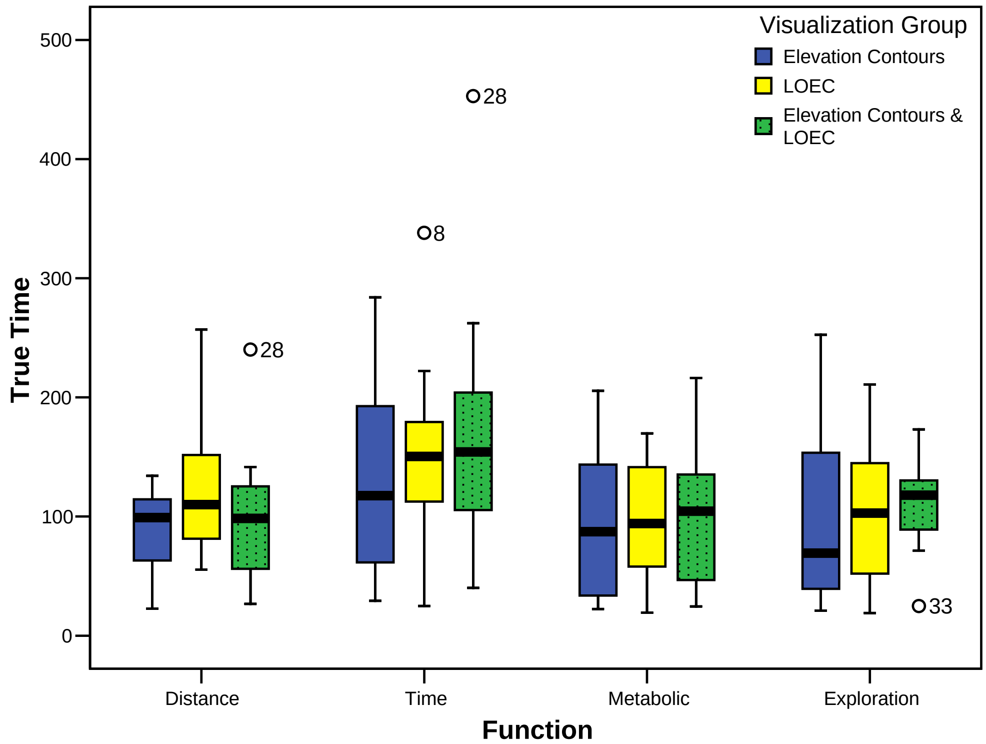

Figure 6.18 Box-plot of true times between visualizations and cost functions, Phase 1

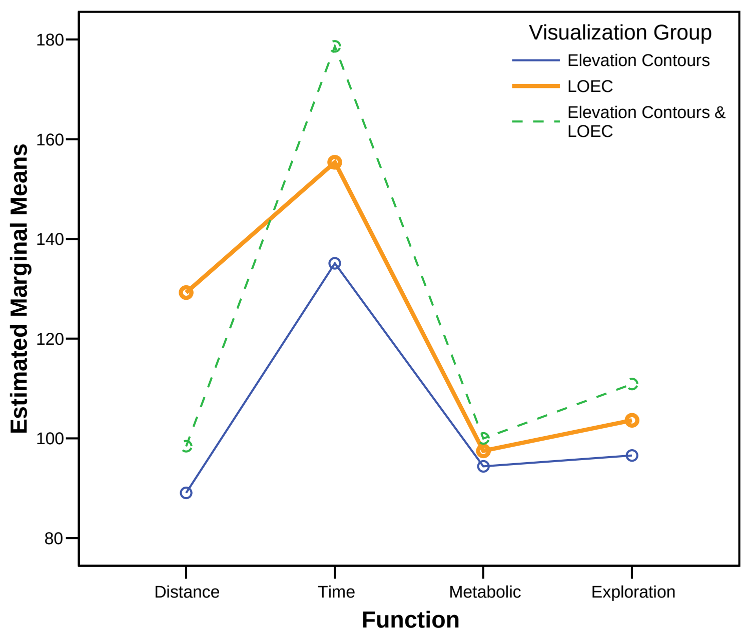

Figure 6.19 Means plot of true time across visualizations and cost functions, Phase 1

6.3.4.2 Phase 2

The range of true times between scenarios, visualization and cost functions can be seen in Figure 6.20. A repeated measures ANOVA (2 x 2 x 3, scenario x cost function x visualizations, Figure 6.21) revealed no main effect based on visualization, but there was a significant difference between cost functions ($p < 0.0001$) and scenario ($p = 0.04$). There were no significant interactions. The difference between cost function is the same as seen in the nominal case, i.e., Time had longer true times than the Exploration function. With respect to scenario, the nominal true times were longer than the off-nominal ones. For the Time cost function, the decrease was on average, 30 seconds, while for Exploration, it was 20 seconds.

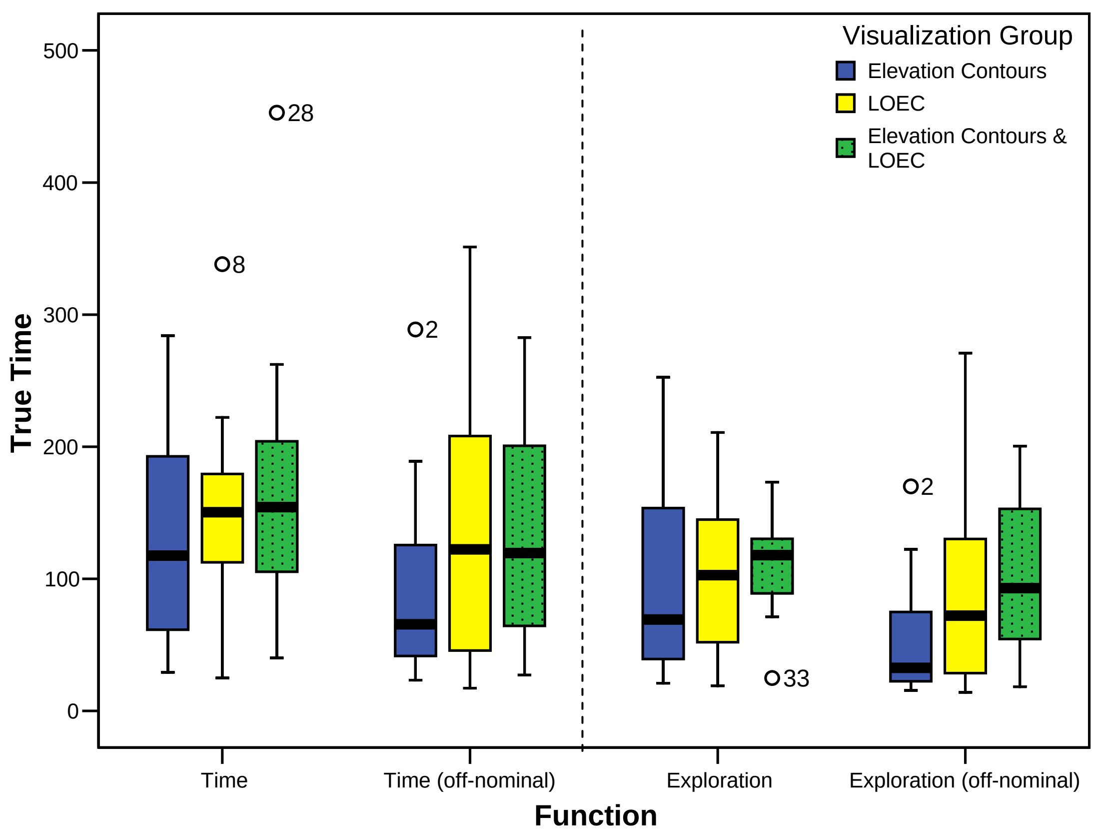

Figure 6.20 Box-plot for true time between visualization and scenario type, Phase 2

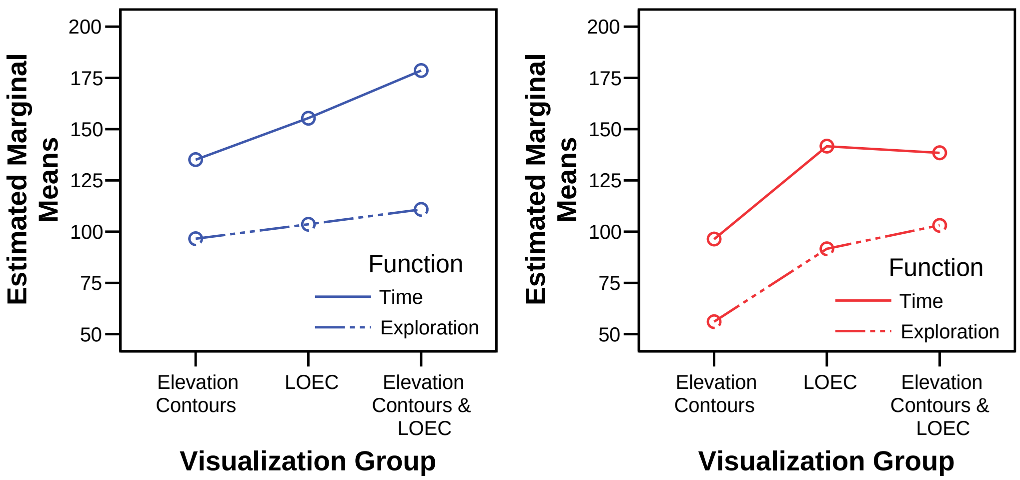

Figure 6.21 Means plot of true time across visualizations, cost functions and scenarios, Phase 2 (Nominal, left; off-nominal, right)

6.3.5 Differential Cost

Differential cost is a dependent measure calculated from the path cost profiles. It is the path cost error difference (in percent) between the first path cost the participant made for a particular trial and the submitted path cost. This metric helps to assess how much path cost error decreased during the optimization process. A negative differential cost would indicate that the participant submitted a path that was worse than the first one they had made. A small differential cost would indicate that the participant's first path attempt was close in cost to the submitted least-costly path.

6.3.5.1 Phase 1

The range of differential costs for the different cost functions across visualization can be seen in Figure 6.22. ANOVA assumptions were not met, thus non-parametric tests were used.

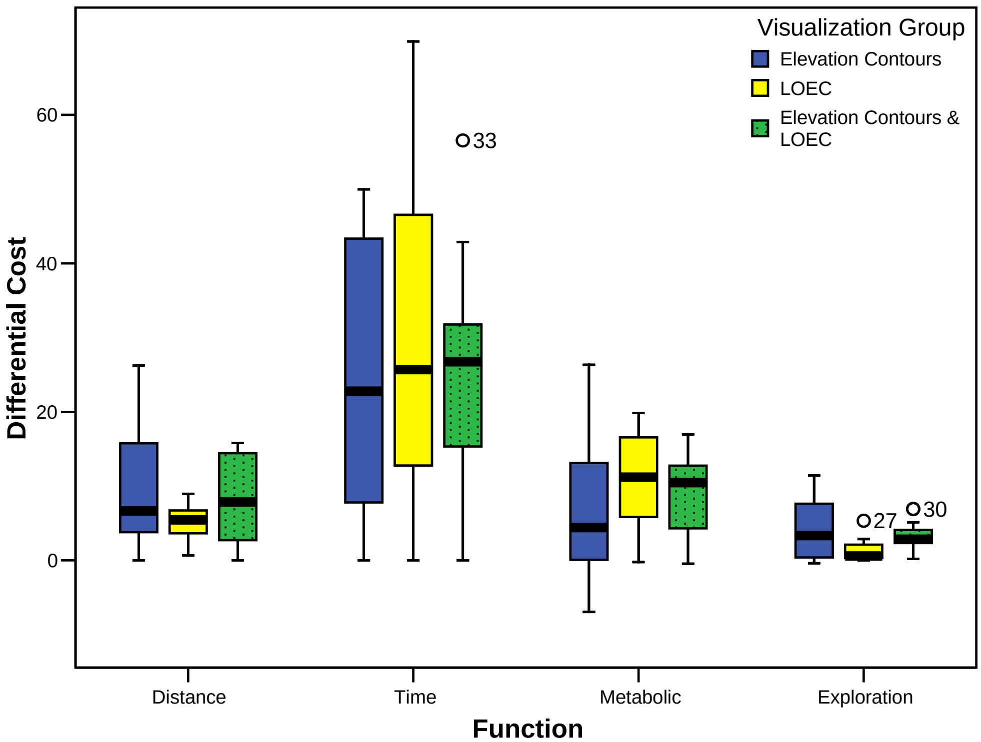

Figure 6.22 Box-plot of differential costs between visualizations and cost functions, Phase 1

There was only one participant that had a large negative differential cost[1] within the Metabolic cost function, likely a mistake on selecting a path to submit. There were participants with zero differential costs, meaning that these participants submitted the first path they created (2 in Distance function, 4 in Time function, 5 each for Metabolic and Exploration functions). The number of participants with zero differential costs was counted, and a Pearson's chi-square test did not show a difference in distribution between visualization groups among the participants who had zero differential costs.

Kruskal-Wallis tests within each cost function revealed only a marginally significant differential cost between visualizations for the Exploration cost function ($p = 0.082$) and none for the other three functions. Comparisons between visualizations (Mann-Whitney tests) showed that the LOEC

[1] There were three additional subjects with negative differential costs but these were at most -0.5%, i.e., essentially zero.

visualization group had a significantly lower differential cost than the visualization group with elevations contours & LOEC ($p = 0.02$). No difference was detected between elevations contours group and the combined visualization group.

A Friedman test was used to determine a significant difference in ranking between the cost functions, regardless of visualization ($p < 0.0001$). All pair-wise comparisons (using Wilcoxon Sign tests) were statistically significant ($p < 0.0001$) except between Distance and Metabolic cost functions. This implies that Time trial had the larges differential cost, Exploration had the smallest, and there was no statistical difference between the differential costs for Distance and Metabolic functions.

In summary, Distance and Metabolic had overall the same differential cost, while Time had the largest. In the cost function with the smallest differential cost, Exploration, there is a marginal main effect of visualization. Comparisons revealed that participants with just the LOEC visualization had a significantly smaller differential cost than the participants in the elevation contours & LOEC visualization group. This implies that these participants started out making better paths for the Exploration cost function than the combined visualization group.

6.3.5.2 PHASE 2

Figure 6.23 show box-plots of the differential cost range found for the two cost functions tested in the nominal and off-nominal scenarios. In the off-nominal case there was a greater number of negative differential costs, indicating the paths that were submitted were higher in cost than the first initial path cost. In the Time off-nominal trial, 6 participants had negative differential costs, while in the Exploration off-nominal, 12 participants. The number of participants with negative differential costs (Figure 6.24) was counted for each visualization group. No significant difference was detected in the number of participants within each visualization with negative differential costs. This implies that negative differential costs among the off-nominal trials cannot be attributed solely to visualization group.

Figure 6.24 also depicts the number of participants that had a differential cost of zero, indicating that they submitted the first path they made as their optimized solution, possibly not optimizing at all. In the Time off-nominal trial, there were 6 participants that had differential costs of zero, while in the Exploration off-nominal trial, there were only 3. There was no statistically significant difference across scenarios for the number of participants with zero differential costs. These participants were also evenly distributed between visualizations. Thus, similar to negative differential costs, zero differential costs in the off-nominal trials cannot be solely attributed to visualization.

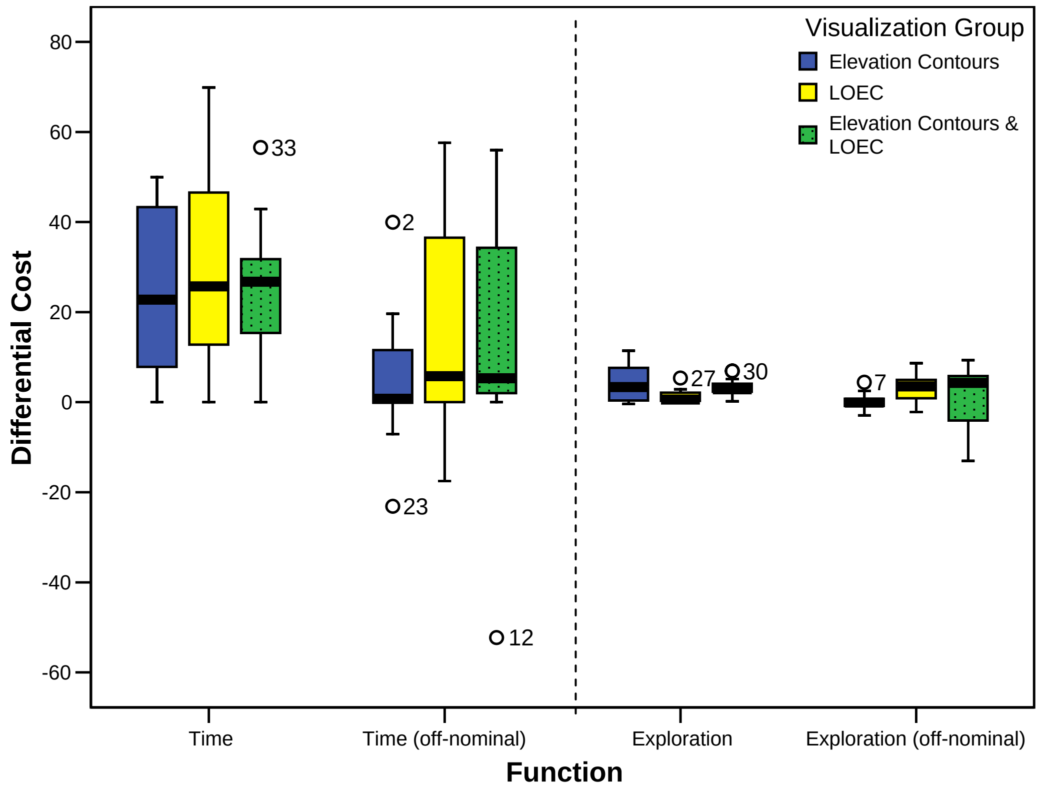

Figure 6.23 Box-plot of differential costs between visualization and scenario type, Phase 2

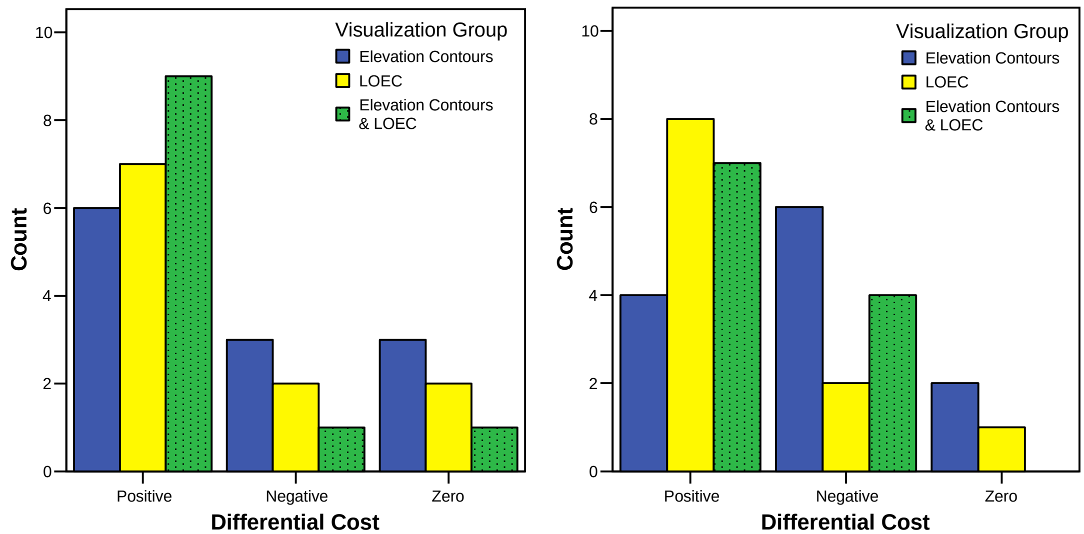

Figure 6.24 Histogram by visualization group of number of participants with negative or zero differential costs in off-nominal trials (left, Time cost function; right, Exploration cost function)

Using Kruskal-Wallis tests, no differences between visualizations were detected in the off-nominal trials with respect to differential cost. This result differs from the nominal case where a marginally significant difference was found for the Exploration function. The difference between off-nominal cost functions was the same as in Phase 1, and the Time cost function had overall significantly larger differential costs (Wilcoxon Sign test, $p = 0.019$). Within each visualization, however, no significant differences across cost functions were detected.

Wilcoxon Sign tests were used to compare differential costs across scenarios. Participants, as a whole, significantly decreased their differential costs in the off-nominal condition within Time cost function across ($p = 0.008$). However, this trend was not exhibited within the Exploration cost function where there was no significant difference between scenarios. Within the elevation contours visualization group, there was a decrease in differential costs across scenarios (marginally significant, $p = 0.062$, for the Time function and significant, $p = 0.01$, for the Exploration function). Within the LOEC visualization group, no significant difference was detected between scenarios for the Time cost function, yet there was a marginal significant ($p = 0.074$) increase across scenarios within Exploration function. Within the third visualization group (both elevation contours and LOEC), there was no difference in differential costs across scenarios.

In summary, within the off-nominal trials, no differences in differential costs were found between visualizations. Across cost functions, the Time function had higher differential costs than Exploration function, which is consistent with Phase 1. Across scenarios, there was a significant decrease in mean differential costs for Time function but no difference in Exploration. A decrease of differential cost for the off-nominal case would indicate some learning (as participants would have been initially close to their solution). However, there was an increase in negative differential costs for the off-nominal condition (from 1% to 26%), meaning that these poor performers decreased the differential costs.

6.3.6 NON-OPTIMAL SATISFICING

Non-optimal satisficing refers to actions taken by a participant attempting to find a lower path cost after a minimum was already achieved. Specifically, non-optimal satisficing is defined as 1) cost surplus: the difference between the minimum path cost achieved and the submitted path cost, and 2) time surplus: the percent of time spent between those ([total time – true time]/total time). For non-optimal cost surplus, non-parametric tests were used. For non-optimal percent time surplus, ANOVA was implemented. If the sphericity assumption was not met, the Greenhouse-Geisser adjusted p-value is reported.

6.3.6.1 PHASE 1

The range[1] of non-optimal satisficing cost surplus is seen in Figure 6.25. In Phase 1, there was little difference between the true minimum cost achieved and submitted cost. The median for all conditions was zero. Hence, participants generally submitted the minimum path cost they had already achieved. No further analysis was conducted on this measure for this Phase 1.

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[1] Three data points in the elevation contours group were identified as outliers (4.07*SD, 3.71*SD, and 5.59*SD above the mean) and hence, removed.

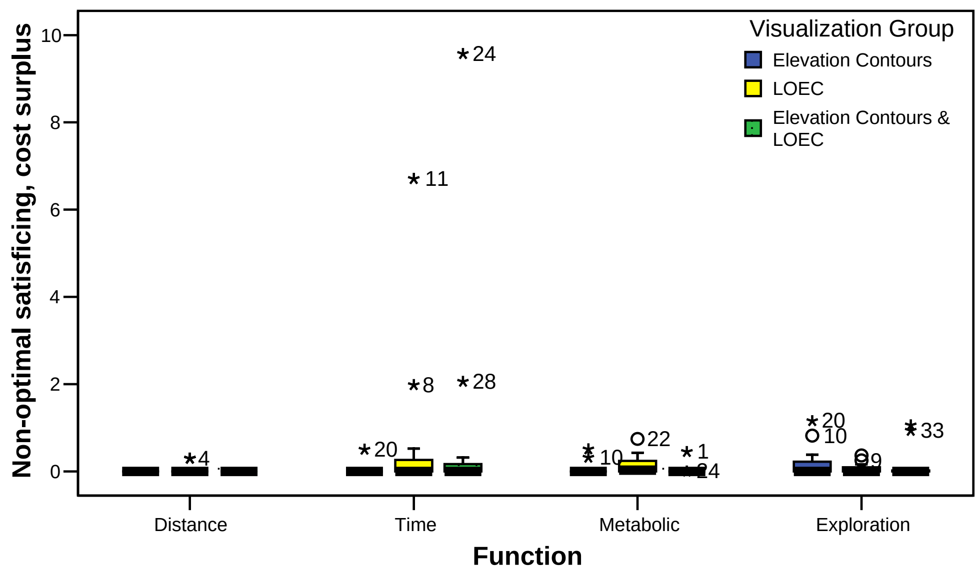


Figure 6.25 Box-plots of non-optimal satisficing, cost surplus, between visualizations and cost functions, Phase 1

The range of non-optimal satisficing for percent of time surplus can be seen in Figure 6.26. A repeated measures 3 x 4 ANOVA was used to test the differences between visualization and cost functions (Figure 6.27). A main effect was found for cost function ($p = 0.046$) but none for visualization. There were no significant interactions. A simple contrast showed that Time cost function had a significantly smaller percent time surplus in non-optimal satisficing when compared to Metabolic ($p = 0.001$) and Exploration ($p = 0.018$), but not Distance. No other significant differences were detected between cost functions.

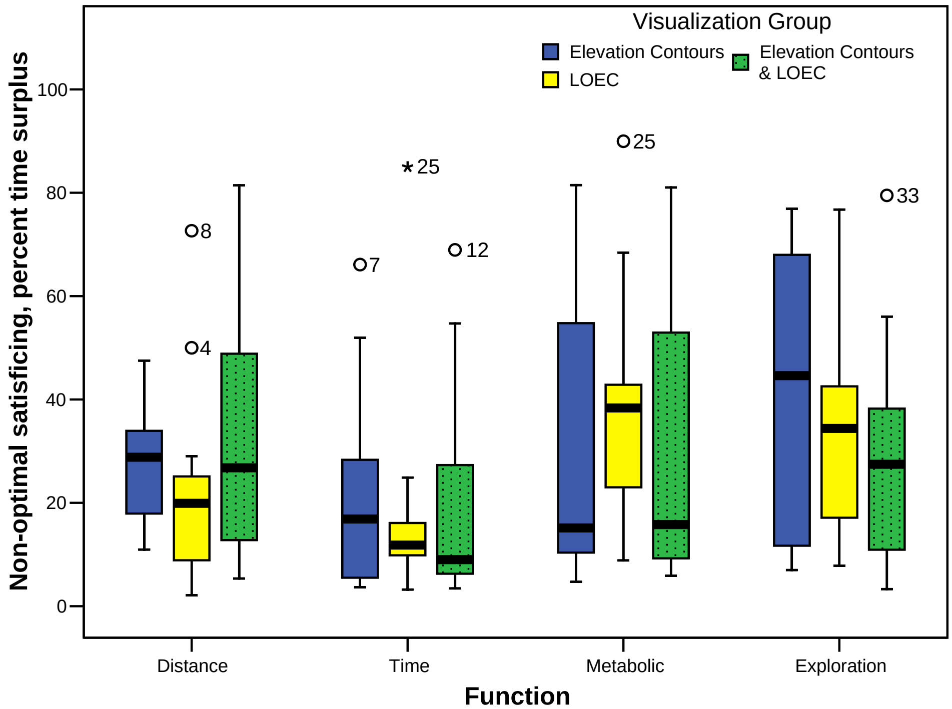


Figure 6.26 Box-plot of non-optimal satisficing (percent time surplus) between visualizations and cost functions, Phase 1

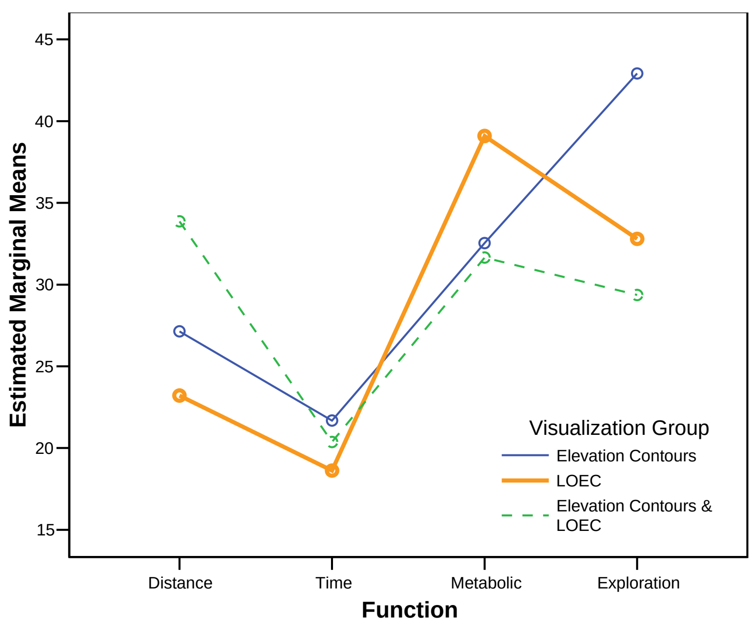


Figure 6.27 Means plot for non-optimal satisficing (percent time surplus) between visualization and cost functions, Phase 1

It is interesting to note that for the Exploration cost function, the mean percent time surplus in non-optimal satisficing increases for just the elevation contours group. A pair-wise comparison within this visualization indicated significant differences between Exploration and both Time ($p = 0.055$) and Distance ($p = 0.041$).

In summary, for Phase 1, participants did not submit sub-optimal path costs relative to the achieved minimum. They did however, spend on average between 20 – 35% of their time conducting non-optimal satisficing. The lowest of these percent time surplus was found within the Time cost function, which was significantly lower than Metabolic and Exploration trials. This difference between cost functions for percent time surplus in conjunction with the previous result where Time function had the largest true time, suggests that participants were feeling the time pressure of completing their optimized path as fast as possible. In other words, after spending a long time attempting to solve the Time function path, participants did not spend additional time conducting non-optimal satisficing once a minimum path was found. This is supported by a significant correlation within the Time function between non-optimal satisficing time surplus and true time (Pearson correlation = -0.48, $p = 0.005$).

6.3.6.2 PHASE 2

The range[1] of non-optimal satisficing cost surplus measures (cost differences between minimum cost found and cost submitted) are shown in Figure 6.28. The non-parametric test, Kruskal-Wallis, did not detect a significant difference between visualizations within the off-nominal scenario. Comparisons across scenarios (Wilcoxon Sign tests) revealed that there was a significant increase in cost surplus for both Time ($p = 0.032$) and Exploration ($p = 0.011$), meaning the cost surplus was higher for both functions in the off-nominal scenario. This increase in cost surplus was about seven-fold for each of the cost functions. Within the off-nominal scenarios, paths made in the Time cost function had a significantly higher cost surplus than Exploration function (Wilcoxon Sign test, $p = 0.001$).

[1] Three outliers were removed (3.71*SD, 4.15*SD, and 4.48*SD above the mean).

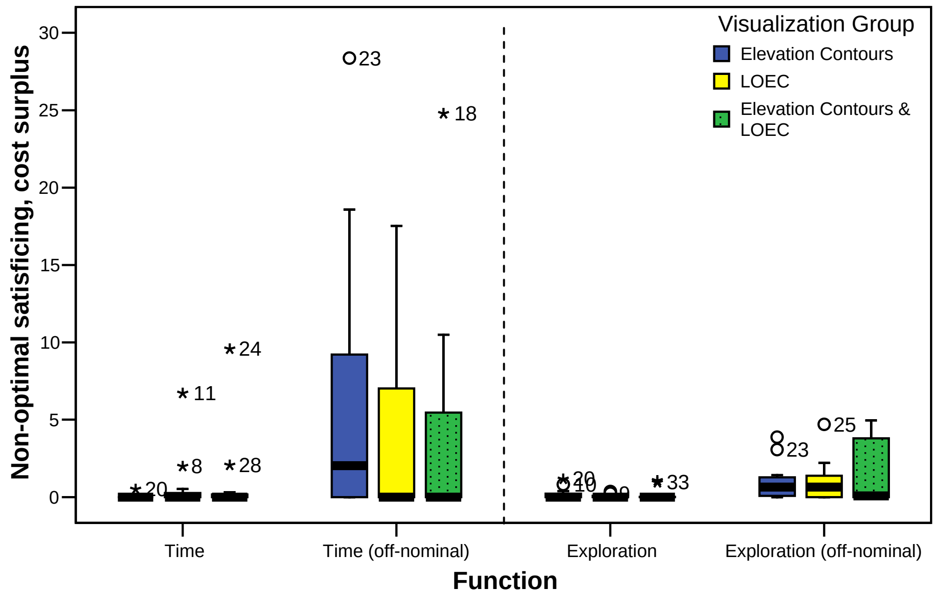


Figure 6.28 Box-plot of non-optimal satisficing (cost surplus) between visualizations and scenarios, Phase 2

The range of the percent time spent conducting non-optimal satisficing is shown in Figure 6.29. Differences in scenario, cost function, and visualization were tested using a repeated measure ANOVA (2 x 2 x 3, scenario x cost function x visualization, Figure 6.30). There was a significant difference between cost functions ($p = 0.007$), where the percent time surplus is smaller for the Time cost function than Exploration, which is the same effect seen in Phase 1. No difference across visualization was detected and no interactions were significant. There was a significant difference across scenario ($p = 0.033$), meaning that in the off-nominal scenarios, the percent time spent in non-optimal satisficing increased. There was a significant correlation between time surplus and true time ($p < 0.0001$).

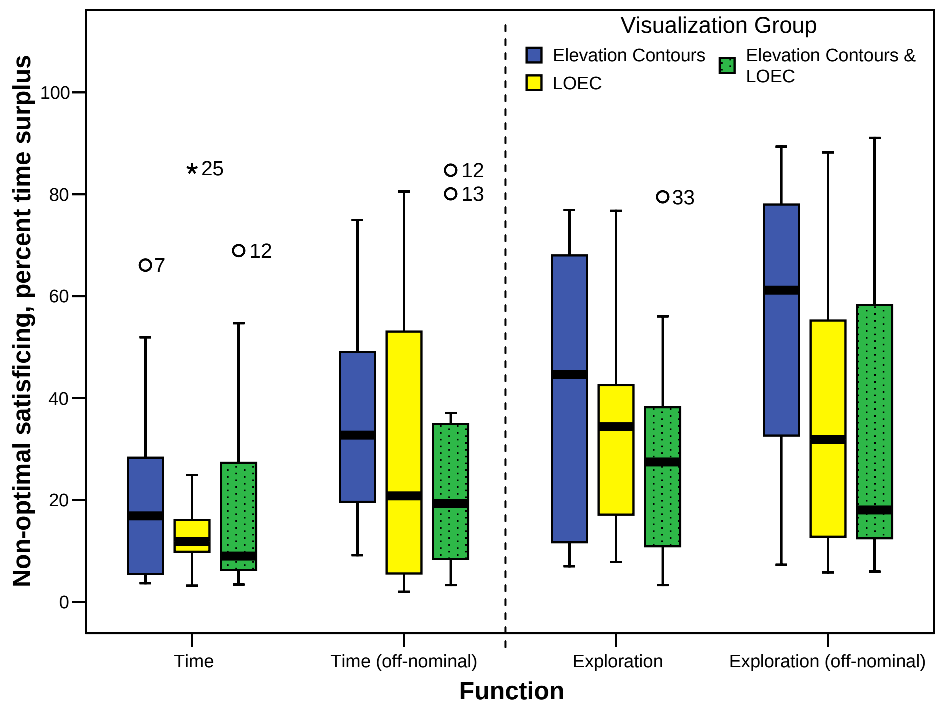


Figure 6.29 Box-plot for non-optimal satisficing (percent time surplus) between visualizations and scenarios, Phase 2

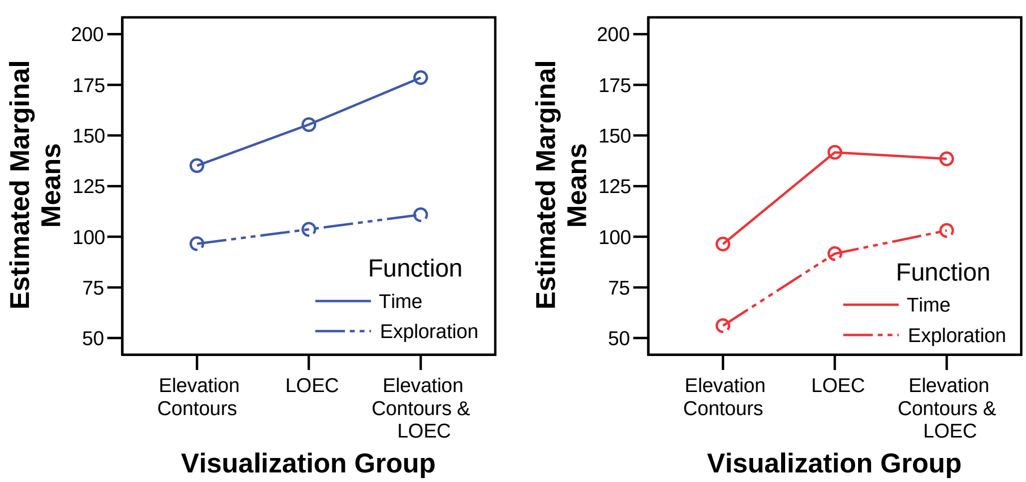


Figure 6.30 Means plot of non-optimal satisficing (percent time) between visualizations, cost functions, and scenario (nominal, left; off-nominal, right)

In summary, across scenarios, more non-optimal satisficing occurred from nominal to off-nominal scenarios. Under degraded automation conditions, participants introduced cost errors not seen in the nominal case which is represented in the seven-fold increase of cost surplus in the off-nominal scenarios. Within the off-nominal trials, the Time cost function had a significantly larger cost surplus as compared to the Exploration function. With respect to percent time surplus, Time cost function trials had a smaller percent time spent non-optimal satisficing (compared to Exploration) and no difference in visualization was detected. Across scenarios, there was a significant increase in non-optimal percent time surplus for the off-nominal trials. In the off-nominal case, participants generally spent the same percent time modifying paths across scenarios, but did not realize that they had reached their minimum path cost, resulting in an increase of non-optimal time surplus.

6.3.7 OTHER ANALYSES

There are a few other analyses worth mentioning that were conducted to further investigate how participants performed in this second experiment.

6.3.7.1 PATH COST ERRORS AND TOTAL TIME CORRELATIONS

Correlations between path cost errors and time (i.e., time penalty, true time, and actual time) were conducted in order to assess if longer time on the optimization task was proportional to a decrease in errors. The path cost errors were not normally distributed (Kolmogorov-Smirnov test, $p < 0.0001$). Furthermore, time penalty and true time were not normally distributed ($p = 0.001$ and $p = 0.037$, respectively). Thus, correlations were analyzed using Spearman's rho correlations (equivalent non-parametric test for Pearson's correlation). There were no significant correlations between errors and any of the time measures.

6.3.7.2 PREFERENCE BETWEEN VISUALIZATIONS

Within the group that had both visualizations, elevation contours and LOEC, participants were asked if they preferred the elevation contours more than the LOEC. Eleven participants answered this question (Figure 6.31), and no statistical difference between preferences ($\chi^2(3, 11) = 0.15$, $p = 0.96$).

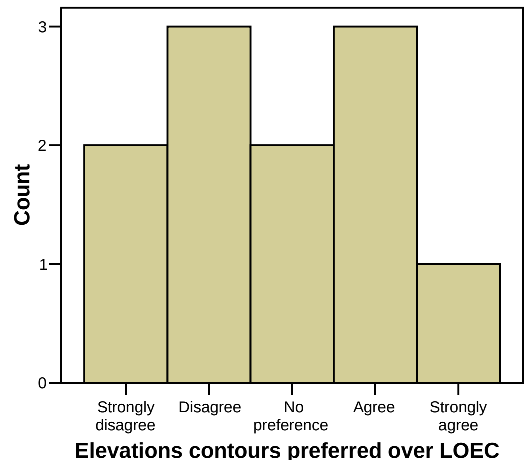


Figure 6.31 Histogram of response for visualization preference within group that had both elevation contours and LOEC.

6.3.7.3 COST FUNCTION TAB

Every interaction between the participant and the PATH interface (every click) was recorded, thus total number of clicks per interface element (i.e., a particular button) could be assessed. This could potentially provide insight to what elements of the interface were used often or not at all. Of particular interest was the number of times the cost function tab (top left corner of interface, Figure 6.1) was clicked because a high count would indicate that the participant needed detailed information about the cost function itself. In general, this information was not accessed during the test trials though it was for the practice trials, regardless of visualization. Even in the practice trials, the number of times is small. For the off-nominal trials, most participants did not click on this tab either.

6.4 COGNITIVE STRATEGIES

Based on observation, participant debriefs, and experimental data, the following path planning strategies were surmised. As in the first experiment, most participants typically created one or two paths and then proceeded to modify waypoints, i.e., manual sensitivity analysis. However, it was observed that there were some participants that chose not to modify their paths much, if at all. This is not say these participants did not do sensitivity analysis, but rather conducted a "whole-path" sensitivity analysis by making multiple path alternatives.

If the percent time spent modifying paths (a measure of the participant's manual sensitivity analysis) is averaged per participant over all six test trials, a bimodal distribution emerges (Figure 6.32). Participants that conducted manual sensitivity analysis (modified path by adding, deleting, and/or moving waypoints) are the ones with average modifying times greater than 16%, which is three-fourths of the total number of participants. Of the participants that conducted "whole path" sensitivity analysis (with average modifying times less than 16%), five were in the elevation contours group, two were in the LOEC visualization group, and only one was in the third visualization group. Using a Pearson's chi-square test, no statistically significant difference in participant distribution across visualizations was detected ($\chi^2(2,34) = 3.64$, $p = 0.16$). Additionally, Mann-Whitney tests did not detect any performance differences (with respect to path cost errors) between the participants that chose manual versus "whole path" sensitivity analysis.

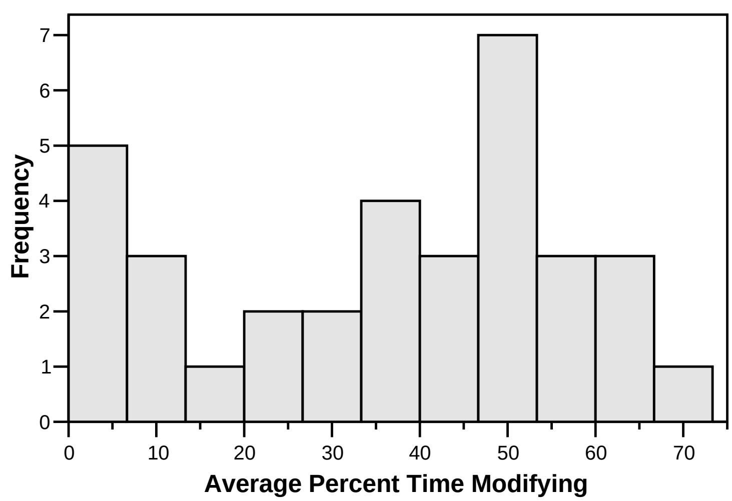


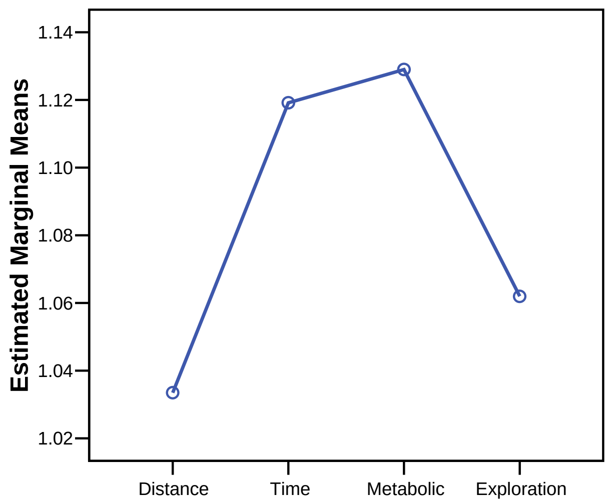
Figure 6.32 Histogram of average percent time modifying across all trials

Of the participants that did conduct manual sensitivity analysis, they primarily focused on modifying single waypoints. Multi-waypoint modifications were observed, but it was not the most prominent strategy. During the experimental debriefs, some participants mentioned that waypoints were moved or added based on the visualization presented. Those participants that had LOEC, for example, would try to move waypoints into areas that were "more yellow" (smaller total cost to the goal) and move away from "purple" (higher total cost to the goal). For those participants that had elevation contours, they would try to keep waypoints between contours, in essence, attempting to make "flat" paths (with small elevation changes). During degraded automation, participants, mainly those with LOEC visualization, mentioned in their debriefs that they leveraged the path elevation profile to make their least-costly paths. In this case, the waypoints were added and moved based on path elevation profiles, where participants were attempting to make their paths "flatter", i.e., reducing changes in elevations.

Aside from using elevation contours and the LOEC colors to make and modify paths, many participants commented on also having used the simple heuristic of "shortest path". For example, an LOEC participant summarized his/her strategy as attempting to make the shortest path to a yellow area. The choice of this heuristic is not surprising because, even though all the cost functions (aside from Distance) had some relationship to slope: in general the longer the path, the higher its cost. Furthermore, this is representative of a "fast and frugal" heuristic (Chase, Hertwig, & Gigerenzer, 1998; Gigerenzer & Goldstein, 1996), where the operator implements a heuristic that he/she recognizes quickly or considers simple. For the case of path planning, finding the shortest distance is a task that is perceptually driven and which humans perform well (see also section 2.2), and hence, is a relatively simple and familiar strategy to implement.

Testing if participants utilized the simple heuristic or strategy of shortest distance, particularly for the more complex cost functions such as Metabolic and Exploration, can be quantified. This can be done by comparing a participant's solution to an objective shortest path solution. If the difference between these costs is small, then the participant was classified as having implemented a shortest path heuristic. Thus for all trials, the shortest path distance was determined and every path submitted as a solution by the participants per test trial was retrospectively recalculated for the Distance cost function (i.e., the length of each test trial path). Comparing the length of submitted path to the shortest distance possible resulted in a distance error (in the case for Distance, this is the same path cost error found for this trial).

Comparisons between conditions were done using a repeated measures ANOVA (see Appendix B for details). Within the nominal trials (left, Figure 6.33), there was a significant difference across cost functions ($p < 0.0001$). Simple contrasts reveal that the distance errors for all the cost functions were significantly larger than Distance (Time, $p < 0.0001$; Metabolic, $p < 0.0001$; Exploration, $p = 0.011$). All other comparisons were significant ($p < 0.0001$) except between Time and Metabolic ($p = 0.40$). These results indicate that participants were implementing other heuristics aside from the shortest path strategy for the other cost functions, though at a lesser extent for the Exploration cost function.



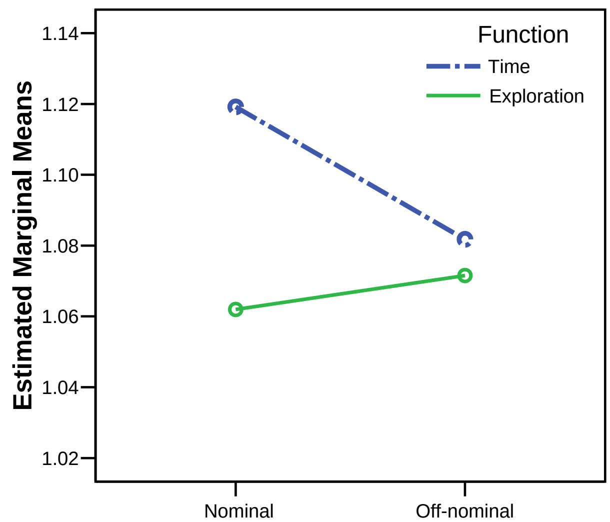


Figure 6.33 Means plot for distance errors (right, nominal cost functions; left, off-nominal cost functions across scenarios)

Distance errors were compared across scenarios in order to determine if participants consistently applied a shortest path heuristic. For the off-nominal conditions, there was a significant difference across cost function ($p < 0.0001$) and a marginal difference across scenario ($p = 0.09$), though there was a significant interaction between these conditions ($p = 0.004$). Point-wise comparisons showed that there was a significant difference across scenarios within the Time cost function only ($p = 0.003$) and not Exploration ($p = 0.36$). This results means that under off-nominal conditions, there was no change in heuristic for the Exploration trial, while for Time, participants tended to make shorter paths and thus relying on the shortest heuristic more[1].

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[1] A similar test was conducted for a second possible heuristic: "following contours". For each subject and trial, the submitted path was categorized as following or not a contour (elevation or LOEC, depending on the visualization). Some similar results as these presented emerged, which was

6.5 PARETO FRONT ANALYSIS

The two key measures of path planning performance in this experiment were path cost errors and total task time. In order to better understand the relationship between these measures, individual participants along a Pareto front were assessed. The Pareto front is the set of non-dominated solution points; in this case, if comparing task time and cost error, a non-dominated point would be the smallest error achieved at a particular task time. Additionally, examining the Pareto front will help understand the effect of visualization, cost function, and scenario in terms of the best performers as opposed to identifying the main effects. Since the task was time pressured, assessing how participants conducted the path cost-time trade would be beneficial to the overall understanding of the human optimization process.

Participant performance was plotted with respect to total task time and path cost errors. A participant is included in the Pareto front if no other participant was able to reach a smaller path cost error in a faster time. It is worth noting that occurrence in the Pareto front does not necessarily mean that the participant performed overall well. The best participant would be one that had a very small cost error in a short period of time.

6.5.1 NOMINAL SCENARIO

The scatter plot of path cost errors versus total time was generated for each nominal cost function in order to determine which participants were on the Pareto front. The Pareto fronts for the Distance and Metabolic cost functions (Figure 6.34) were "flat", meaning that the participants along the front have relatively the same path cost with increasing total time. In other words, regardless of the time spent on the optimizing task, path cost errors do not improve much. This is expected from the Distance cost function, which was the easiest cost function for participants to optimize. In the Distance Pareto front, there were participants from all three visualizations. In the Metabolic Pareto front, there were two elevation contours participants with path cost errors of 5.2% and 4.2%

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not unexpected participants often applied both types of heuristics (shortest path and following contours).

(subjects 5 and 19 in Figure 6.34), taking 59 and 93 seconds, respectively. These two participants did not spend any time modifying paths (just making a few whole paths). The third participant (subject 8) in the Metabolic Pareto front had the smallest error 4.0% (in the LOEC group), however he/she spent 256 seconds on the task and 75% of it modifying the path. For the Metabolic cost function, the best performers were in the elevation contours and additional manual sensitivity analysis helped decrease the path cost errors but not by a large amount.

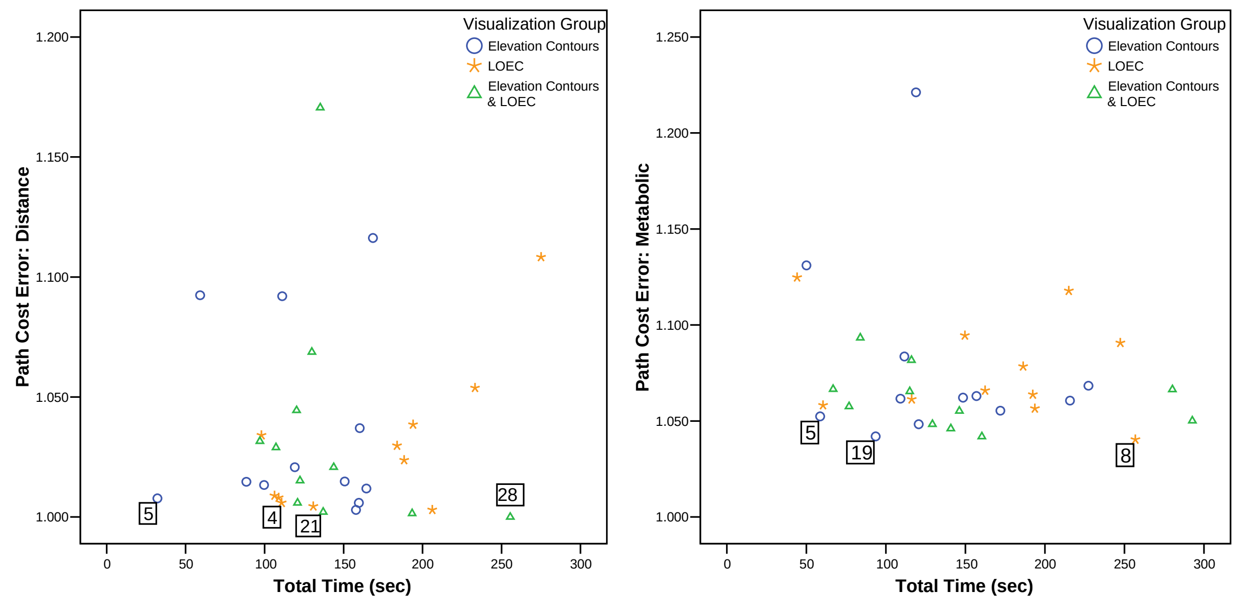

Figure 6.34 Scatter plot of path cost errors and total time for Distance (left) and Metabolic (right) cost functions

The Time and Exploration cost functions have a clearer Pareto front (Figure 6.35). The set of Pareto points for the Time cost function (left, Figure 6.35) identified three participants in this non-dominated front, all in the elevation contours visualization group. In decreasing order, the cost errors drop from 37.1% to 33.1% to 26.2% (subjects 17, 10, and 20, respectively[1]). Compared to the first participant, total times spent completing the task triples and quintuples for improvements of 4% and 11%. The trend with respect to percent time spent modifying was 0% to 56% to 62%. Thus, the main difference between these participants is the amount of time spent making single

[1] It is important, though, to note that the average path cost error for this trial was 60%.

waypoint modifications. Increased time and modifications resulted in decreased cost error. It is surprising that subject 17 did well in the Time cost function, the trial with the largest errors; he or she was the only participant that self-designated as having no map or hiking experience and did not do particularly well in other trials, especially the Metabolic trial. Nonetheless, the exhibited trend was that increased manual sensitivity within the elevation contours participants led to improved path planning performance.

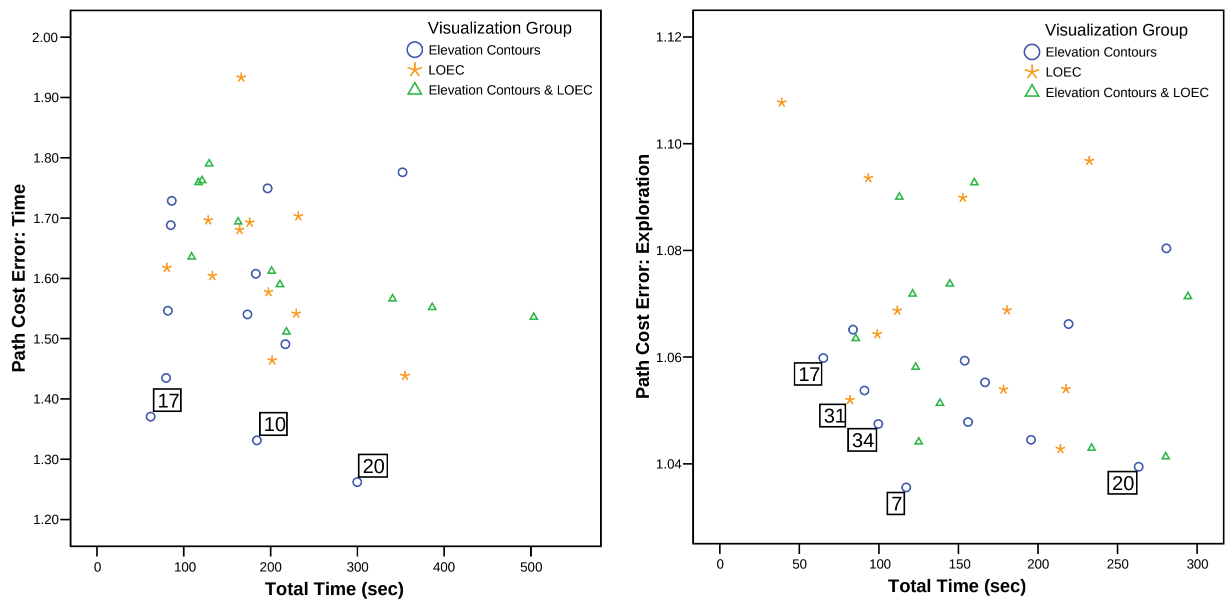

Figure 6.35 Scatter plot of path cost errors and total time for Time (left) and Exploration (right) cost functions, nominal cases

In the Pareto front for the nominal Exploration cost function (right, Figure 6.35), there was a participant that stands out as having superior performance (subject 7 in elevation contours group). However, this participant performed poorly for the Time and Exploration cost functions. Thus, the Pareto front for the Exploration function is considered with and without this participant.

If considering subject 7, the Exploration function Pareto front, three of the four participants were in the elevation contours group. A reduction of path cost errors was accompanied by about 20-second increase in total time spent optimizing. The path cost errors along the Pareto front were 6.0%, 5.2%, 4.8%, and 3.6% with corresponding total task time of 65, 82, 100, and 117 seconds (subjects 17, 31, 34, and 7 in Figure 6.35). The first two participants did no path modifications while the other two spent 5% and 12% of their optimizing time modifying their paths. Thus, though this trend was not as pronounced as in the Time cost function, the overall best Exploration cost function performers were found in the elevation contours group and a slight increase in path modifications led to a decrease in path cost errors.

If considering the Exploration Pareto front *without* subject 7, there was a definite change across the Pareto front. Of this set, the participant with the smallest path cost was an elevation contours participant, with a path cost error of 3.9% (subject 20). However, he/she spent 263 seconds optimizing the path, 68% of it conducting path modifications. This was the same overall trend observed with the other participants, where a large portion of time was spent in manual sensitivity analysis, though without much decrease in path cost errors. Additionally, these other participants were from the LOEC visualization groups. This trend indicates that while participants increased their time optimizing paths through modifications, it led to small benefits with regards to cost. The participants' inability to decrease errors over time indicates that participants understood poorly how to improve path cost errors for the Exploration cost function.

For the nominal scenario, the general trend observed for the Pareto front was that participants with low cost errors and total times were in the elevation contours visualization group. Furthermore, for the Time and (to a lesser extent) Exploration cost functions, a decrease in path cost errors was accompanied by an increase in percent time spent modifying, which can be interpreted as an increase in manual sensitivity analysis.

6.5.2 OFF-NOMINAL SCENARIO

The scatter plots of path cost errors versus total time for the off-nominal Time and Exploration cost functions are shown in Figure 6.36. The Pareto front under the off-nominal scenario for Time was relatively well-defined, yet for the Exploration, it appears to be rather "flat" (i.e., little decrease in path cost errors with time).

For the Time off-nominal Pareto front (left, Figure 6.36), there was a decrease in path cost errors from 39% to 31% to 22%, with corresponding total times of 57 to 88 to 163 seconds (subjects 6, 28, and 20, respectively). Only the participant with the lowest error conducted manual sensitivity analysis, with 33% of his/her time spent modifying paths. The second participant made multiple paths, while the remaining Pareto front participant made only one path. It is important to note that, unlike the nominal case, the participants along the off-nominal Time Pareto front belong to other visualization groups (not just elevation contours). While the trend was not as strong as in the nominal, participants decreased path costs with an increase in sensitivity analysis.

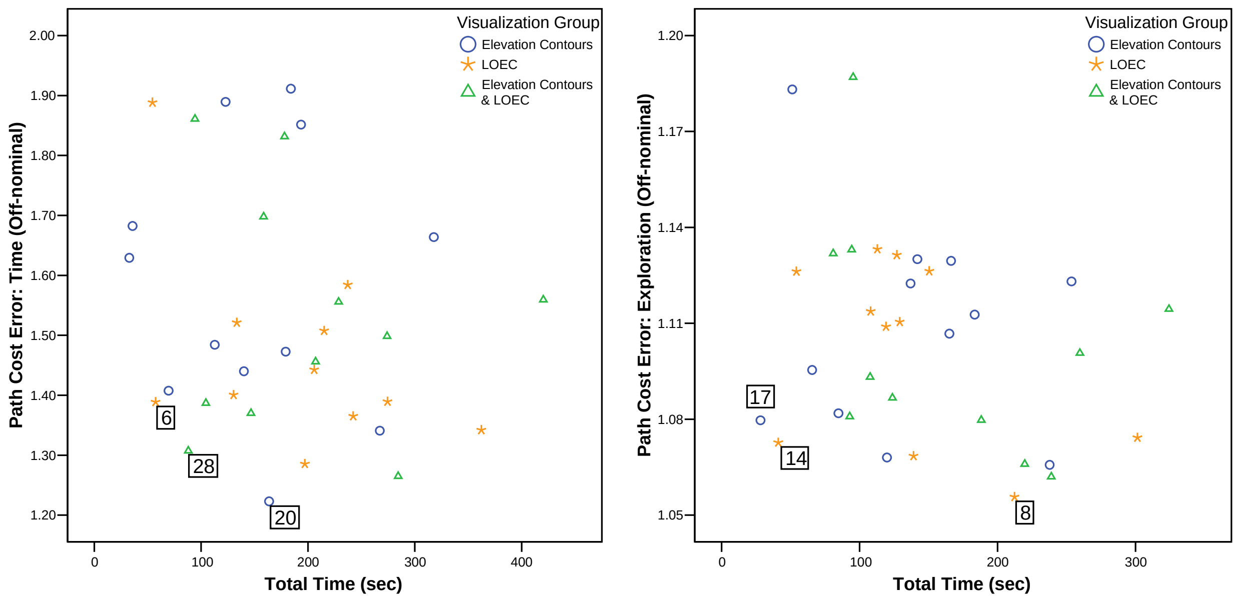

Figure 6.36 Scatter plot of path cost errors and total time for Time (left) and Exploration (right) cost functions, off-nominal cases

For the case of off-nominal Exploration (right, Figure 6.36), two of the three participants in the Pareto front were from the LOEC visualization group. Participants decreased in errors from 8% to 7.2% to 5.6% (subjects 17, 14 and 8, respectively). Correspondingly, the amount of time spent was 28, 41, and 238 seconds. Only the participant with the smallest path cost spent any time modifying paths (70%).

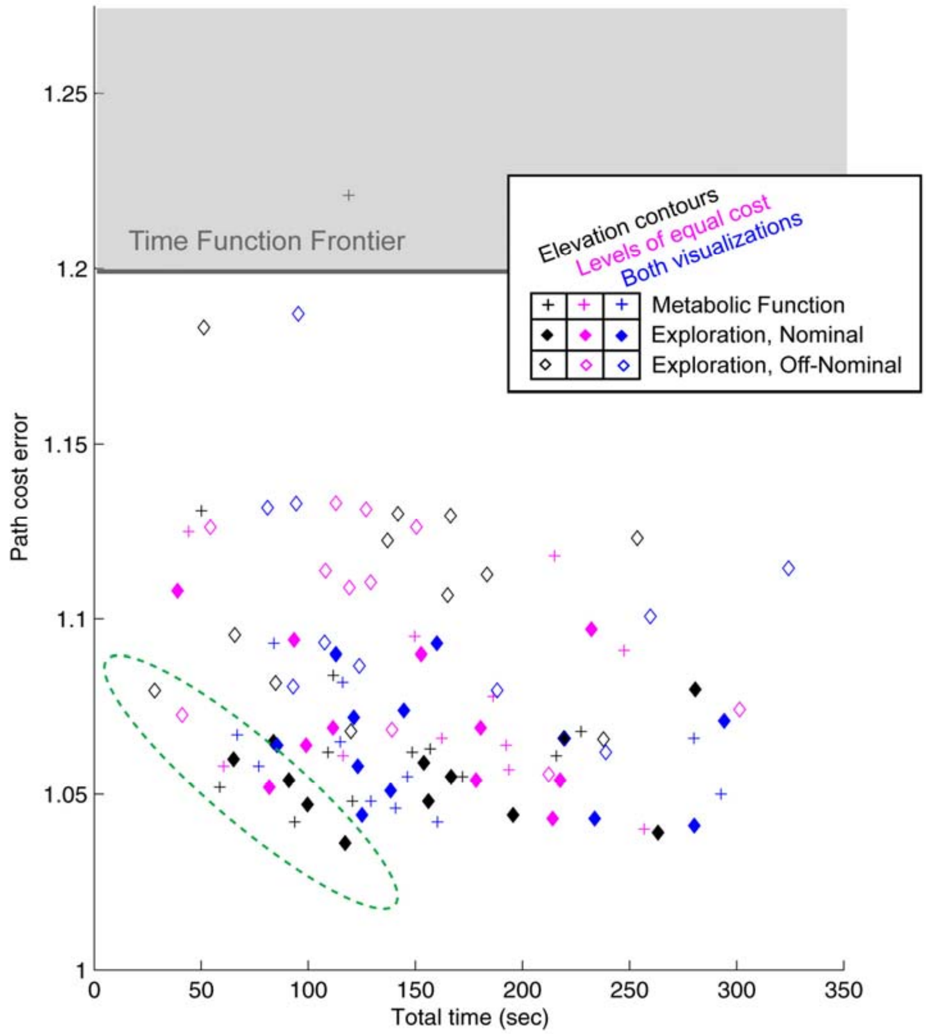

Figure 6.37 Aggregate scatter plot of path cost errors and total time across cost functions, visualization, and scenario (Pareto front circled)

The most important trend observed in the off-nominal cases was the presence of participants that belonged to the other LOEC visualizations. In addition, only the participants with the smallest path cost errors spent large amounts of time modifying paths, i.e., conducting manual sensitivity analyses. The Pareto front analysis suggests that in the nominal case, the best performers (low path cost errors and total time) are within elevation contours, while the LOEC was most useful in the off-nominal cases. If considering the Pareto front with all the independent variables[1] (circle in Figure 6.37), there is a larger representation of participants in the elevation contours group and LOEC visualization group (and only two of the combination visualization group).

6.6 DISCUSSION

The two phases of this experiment address two conditions: one pertaining to path optimization of four cost functions under nominal conditions, and the other, a subset of two cost functions under off-nominal conditions. In both, there were three visualization groups: elevation contours visualization, levels of equal cost (LOEC) visualization, and both. As in the first experiment, it was not practical to test participants in all three of the visualizations. As a result, the visualization method was a between-subject variable. Participants were randomly assigned to one of the visualization groups, balancing the number and gender of subjects in each. Aside from map-use experience, participants were also asked to complete an independent spatial ability test. Neither of these metrics resulted in a viable covariate (i.e., these measures did not predict performance). Furthermore, there was no statistical evidence that there was a visualization group difference with respect to map-use experience, spatial ability test score, nor choice of strategy type. Thus, the participants in this experiment were reasonably balanced across the visualization groups.

6.6.1 NOMINAL SCENARIO

Table 6.3 summarizes the major results for the dependent and independent variables within Phase 1.

[1] Only the most complex functions (Metabolic and Exploration) are shown as these are the most representative of what would be included in an actual path planner. The Time cost function errors were significantly larger, creating a frontier at the top of the figure.

Table 6.3 Summary of results for Phase 1

Dependent Variable	Independent Variable: Visualization (EC, LOEC, Both)	Independent Variable: Cost Function
Path cost errors	No main effect	Time > Metabolic ≈ Exploration > Distance
Time penalty	No main effect	Time > Distance, Metabolic, Exploration
Percent time modifying	No main effect	Within LOEC groups, Time > EC Time
True time	No main effect	Time > Distance, Metabolic, Exploration
Differential cost	Within Exploration: LOEC < Both	Time > Distance ≈ Metabolic > Exploration
Non-optimal satisficing (cost surplus)	No main effect	No main effect
Non-optimal satisficing (time surplus)	No main effect	Time < Metabolic, Exploration ≈ Distance

6.6.1.1 COST FUNCTIONS

It was hypothesized that path planning performance would decrease with the number of variables being manipulated through the optimizing cost function, though this decline would be lessened by the LOEC visualization. Thus, Distance would be the easiest to optimize, followed by Time, Metabolic, and Exploration cost functions. Deteriorated performance would be observed in an increase of errors and time spent on path planning task. Unexpectedly, in this experiment, Time was the most difficult cost function to optimize, as supported consistently through every measure of performance. Difficulty is defined as having the highest path cost errors and time penalty (total time). Participants, regardless of visualization group, had significantly higher path cost errors, time penalty (total time), and true time for the Time cost function. Particularly for the path cost errors, the average magnitude of the Time errors was about ten times larger than the hypothesized more difficult cost functions (Metabolic and Exploration).

As expected, optimizing to the shortest path (Distance) was the easiest for participants, regardless of visualization. Their path cost errors were about 3 ± 3%. This error doubled for Metabolic and Exploration, 7 ± 2% and 6 ± 2%, respectively. Path cost errors for the Time cost functions were 60

± 14%. There was no statistically significant difference between Metabolic and Exploration path cost errors. While there were differences among the path cost errors, no significant difference was found between these three cost functions with regards to time penalty and true time.

Cost function differences were also detected among the path cost profiles measures, specifically differential cost and percent time spent conducting non-optimal satisficing[1]. Differential cost, derived from the path cost profiles, was the percent difference between the last and the first path cost error; it is a measure of "how close" participants were in their first attempt at optimizing the path. Again, Time had the largest differential cost (26.6 ± 19.4%) while there was no difference between Distance (7.66 ± 6.82%) and Metabolic (8.82 ± 7.63%). Surprisingly, the most complex cost function presented to participants, Exploration, had the smallest differential cost (2.97 ± 3.05%). These results imply that for the Time cost function, participants' initial paths were far from their optimal (as compared to the other three cost functions). On the other hand, participants started out relatively close to their submitted path solution for the Exploration cost function. This may have been due to learning, however, the fact that there were significant differential cost differences between Exploration and Metabolic functions even though there was no significant difference in path cost error nor time penalty, implies that participants were not able to improve on the path cost errors for the Exploration function as much as with the Metabolic paths. Thus, while Time was a difficult cost function for participants to optimize, participants still found Exploration a challenging function.

Since participants spent more time attempting to optimize the Time function paths than any other cost function, it would be expected that the invested time would result in small path cost errors. Yet, this was not the case; participants did reduce their initial path errors the most (i.e., largest differential cost) for Time function but the cost errors were the highest. This would suggest that participants could not improve on their solution any more. However, this is not necessarily true as participants might have not spent more time optimizing because of the time pressure. This hypothesis is supported by the fact that within the Time cost function, participants spent a significantly smaller percent of time in non-optimal satisficing (than in the Metabolic and

[1] For cost functions, there was no main effect detected for percent time spent modifying path.

Exploration cost functions). Therefore, it is might be possible for participants to reduce path cost errors for paths based on the Time cost function if they had not been time pressured.

To sum up the cost function effect, based on participants' path planning performance, it appears that participants viewed the Metabolic and Exploration as equally difficult cost functions, yet easier than the Time cost function. This is surprising because Metabolic and Exploration functions were more complex functions, involving three and four variables, respectively, while the Time function only included two (Distance and slope). There is some evidence, with the differential cost metric, that indicates participants found the Exploration function challenging (based on the small differential costs). Nonetheless, overall, the Time function was the most difficult cost function to optimize for all participants.

Performance metrics, however, do not explain entirely why the Time cost function was the most difficult to optimize. One reason may be that humans more intuitively understand how to optimize time. For instance, daily people attempt to find the fastest way from one location to another, such as in driving tasks. Conversely, optimizing a more complex function like Metabolic or Exploration is more of an abstract notion. Participants may have felt they could optimize a path based on Time as opposed to Metabolic and Exploration, and hence, spent more time optimizing the conceptually easier function to understand. The Metabolic and Exploration cost functions may be so intricate that the path planning task may have immediately exceeded the human capacity for understanding how to fundamentally optimize these functions. As a result, the problem became "opaque" and participants relied on the information and tools they were provided (i.e., path costs and visualizations) without giving the problem as much thought and attention as the Time cost function (as exhibited by a lower time spent on task). This would imply that participants would revert to very simple heuristics for the more complex cost functions of Metabolic and Exploration.

Even though participants repeatedly mentioned during their experimental debrief that they used a "shortest path" heuristic, the results imply that some combination heuristic was implemented because the submitted paths were not the shortest paths possible. Comparing across cost functions, the shortest path heuristic seems to have been applied more to the Exploration cost function than to the Metabolic and Time functions. This is consistent with the fact that participants did not fully understand how to optimize the Exploration cost function. The Exploration function relies on sun position, and participants may not have developed a good heuristic for this additional variable. With respect to the Time cost function, the shortest path heuristic was an ineffective strategy because it does not take into account changes in slope which are essential in this cost function. Therefore, even though participants did not primarily use this heuristic for the Time cost function, applying it for a portion of the path results in poor path planning performance.

Poor performance on the Time function may have also resulted from the variability and sensitivity of the cost function to changes in its variables (i.e., slope). This means that when participants attempted to optimize a Time path, small path modifications resulted in large path cost changes. To illustrate this, Figure 6.38 has two screen captures, one for the Time and the other for the Exploration function, that contain two paths each. Below the map, the path cost profiles are also shown. If path costs are compared (in this case to the blue path labeled "base"), one can see that a relatively small path modification (red path) results in a large cost difference. On the other hand, this is not seen for the Exploration function paths, where a path modification resulted in a small cost difference. Thus, within the Time cost function, small changes in slope resulted in a large effect on the total path cost as compared to the other cost function. Cost functions that exhibit this trait could be labeled "overly-sensitive" cost function. Due to the variability, participants could more readily assess the impact of a path modification on the overall path cost (i.e., changes were more salient). For example, this can be observed in the path cost profiles for the Time paths in Figure 6.38. However, this variability also makes reducing the path cost errors more challenging for the participant. This implies that humans under time pressure might be ill-equipped to optimize cost functions, such as the Time cost function, that are very sensitive to small changes in variables.

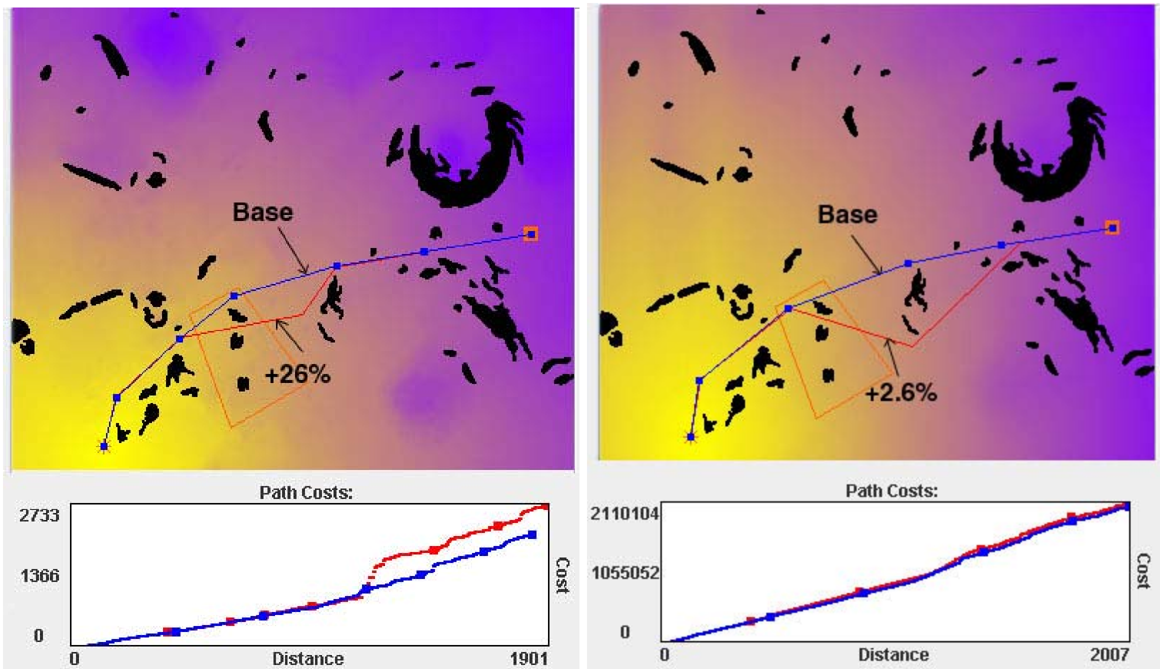

Figure 6.38 Cost differences for path modifications within cost function (left, Time; right, Exploration)

6.6.1.2 VISUALIZATIONS

Overall, visualization did not have a main effect on path planning performance. No significant main effects were found with path cost errors, time penalty, nor true time. Nonetheless, there were some trends based on visualization. With respect to differential cost, a visualization difference was found within the Exploration cost function only, where participants with LOEC visualization had smaller differential costs than participants with both elevation contours and LOEC visualization[1]. This means that participants with LOEC had smaller differences between minimum and first path costs, i.e., they were close to their optimal solution in their first try. This implies that for the LOEC visualization that aggregated multiple variables, it was the most effective for the unusual (and likely, unintuitive as it included sun position) cost function of Exploration. This result is an important finding because it provides evidence that for a multi-variable, intricate cost function, the levels of equal cost visualization at least helped participants start closer to the average minimum cost.

With respect to the amount of time spent on optimizing task, it appears that participants that had the LOEC visualization tended to equalize the amount of time spent on the optimizing task regardless of cost function, while participants that had elevations contours (either with or without LOEC) spent most on Time and Exploration than Distance and Metabolic. Another visualization-based trend was detected in the percent time spent modifying paths. For the Time cost function, participants with the LOEC in their visualization spent significantly more of their time modifying the path than participants with just the elevation contours visualization. These same elevation contours participants also increased their time spent in non-optimal satisficing for just the Exploration cost function. Most importantly, these change in strategies based on visualization did not affect overall path planning performance as there was no main effect based on visualization.

It could be argued that the difference in percent time spent modifying paths by participants with the LOEC visualization did so because the visualization is an additional, novel tool. However, significant differences were only seen within the Time cost function, and not any other cost function. This result is significant when considering how these very same participants performed for the Time cost function in the off-nominal case (discussed in the next section).

The effect of visualization is most evident in the Pareto front analysis, where participants with small cost errors and short task times were evaluated. Under the nominal case, most of the best performers were in the elevation contours group. Furthermore, the participants in the Pareto front set with the smallest cost (though with longer times) were those that had higher percent time spent modifying. This suggests that manual sensitivity analysis, and not just longer task times, is essential to optimizing least-costly paths. It is important to note though that if the participant does not fundamentally understand how to optimize the cost function, they could spend large portions of time modifying paths without decreasing the path costs. This was seen within the participants in the Exploration function Pareto front set. While it was observed that most of the best performers were in the elevation contours group, there was no overall statistical main effect of visualization.

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[1] This trend was not seen for Metabolic cost function.

In summary, most of the best performers (participants with low cost errors and total time on task) were in the elevation contours group. With respect to LOEC, participants that had this visualization tended to spend more time modifying paths for the perceived most difficult function of Time, and helped participants create a first path that was close to optimal for the most complex function, Exploration. Surprisingly, for the Metabolic cost function, another complex function, these trends were not seen. Perhaps the simple, shortest path heuristic for Metabolic function circumvented the need for participants to leverage the LOEC visualization. Nonetheless, the mentioned trends are indications that participants were leveraging the visualization to achieve least-costly paths, although exhibited in different manners for the two cost functions of Time and Exploration. Unfortunately, the visualization was not powerful enough to produce significant difference in path planning performance across all conditions (i.e., decreased path cost errors and total time spent on task).

6.6.2 OFF-NOMINAL SCENARIO

Table 6.4 summarizes the major results for the dependent and independent variables within Phase 2.

Table 6.4 Summary of results for Phase 2

Dependent Variable	Independent Variable		
	Visualization (EC, LOEC, Both)	**Cost Function**	**Scenario**
Path cost errors	No main effect	Time > Exploration	LOEC Time nominal > off-nominal Exploration nominal < off-nominal
Time penalty	No main effect	Time > Exploration	No main effect
Percent time modifying	No main effect	Interaction w/ visualization EC, Time < Exploration LOEC, Time > Exploration Both, Time ≈ Exploration	No main effect
True time	No main effect	Time > Exploration	Nominal > Off-nominal
Differential cost	No main effect	Time > Exploration	Time nominal > off-nominal Exploration nominal ≈ off-nominal # of negative diff. costs nominal < off-nominal
Non-optimal satis-ficing (cost surplus)	No main effect	Time > Exploration	Nominal < Off-nominal
Non-optimal satis-ficing (time surplus)	No main effect	Time < Exploration	Nominal < Off-nominal

For the off-nominal cases, Time and Exploration cost functions were tested. It was hypothesized that path planning performance would decrease within the off-nominal scenario, resulting in participants introducing and increasing cost errors into their path solutions. Furthermore, since participants were explicitly told that they could not depend on the automation (be it the LOEC and the displayed path costs), some evidence of distrust would emerge in their performance, such as increased time on task or more time spent optimizing paths. Based on visualization, it was hypothesized that participants with elevation contours would benefit from their visualization as opposed to those that just had the LOEC visualization. Thus, some automation bias was expected for those LOEC-only participants, in that they would make worse paths since they depended on the erroneous visualization.

6.6.2.1 EFFECTS OF DEGRADED AUTOMATION

Even though participants had an idea of the proportion of the cost function errors, without the ability to rely on the interface to provide accurate path costs, participants had a poor sense of when they had reached a minimum path cost, introducing on average, an additional $5 \pm 8\%$ error in Time and $1.2 \pm 1.6\%$ in Exploration cost functions. Even though these errors are relatively small, the errors were as high as 28% and 5% for Time and Exploration functions, respectively. In addition, true times were significantly shorter in the off-nominal compared to the nominal case, which may be due to some learning since the off-nominal trials were the last ones completed. There was also a significantly higher number of negative differential costs in the off-nominal condition, as compared to the nominal, meaning that participants were submitting paths that were even worse than the first path that was made. This is important because it indicates that there was a decrease in path planning performance under degraded automation conditions. Participants did not know they had reached a minimum path cost, though most were trying to find it, as suggested by the lack of difference in time penalty (i.e., total time) between scenarios.

Interestingly, there was no significant difference across scenarios for the percent of time spent modifying paths. This seems unusual as one might have expected that the distrust in the automation may have led participants to increase time spent modifying, and hence, more manual sensitivity analysis. However, an increase in sensitivity analysis was seen in the metric of percent time spent conducting non-optimal satisficing (i.e., participants attempting to find a lower solution that was never achieved). This was an expected result because participants would distrust the automation's path costs, thus, they would spend more of their time searching for a solution. This apparent disagreement might be due to a shift in type of sensitivity analysis. The most frequent method of conducting sensitivity analysis was modifying paths, the strategy chosen by 26 participants. The other type of sensitivity analysis, creating multiple paths, was only conducted by the remaining 8 participant. The dependent measure of percent time spent modifying only describes the first strategy.

Additional time on the task overall might be expected for the off-nominal condition, yet there was no significant time penalty differences across scenarios. If participants were spending equal time on both scenarios, it could be considered that participants were not adding more effort into finding their path solutions or they could have learned how to optimize the paths. However, this is a time-pressured task, and because of it, participants may have opted not to spend more time in the degraded automation condition.

6.6.2.2 COST FUNCTIONS & VISUALIZATIONS

Between cost functions, the results were consistent with the nominal phase of the experiment. The Time cost function was the most difficult function as it had significantly higher path cost errors, and longer time penalties and true times when compared to the Exploration cost function. However, the assessment between scenarios within each cost function suggests that participants were able to adapt optimization strategies for Time but not the Exploration cost function.

Under degraded automation conditions, it was expected that participants' performance would deteriorate, resulting in longer task times and larger path cost errors. In terms of performance across scenarios, participants did not spend more time in the off-nominal trials as compared to the nominal ones. However, within the Exploration function, path cost errors increased in the off-nominal condition regardless of visualization. Within the Time function, participants performed differently within the visualization groups with regards to path cost errors. Participants with the LOEC visualization decreased their Time path cost errors in the off-nominal condition, while there was no significant difference across scenarios for other two visualizations.

It was hypothesized that since LOEC participants would exhibit some automation bias (by depending on the erroneous, automation-generated visualization to make their least-costly paths), resulting in the largest path cost errors. This was not observed as there were no visualization differences within the Exploration function and there was actually a decrease in path cost errors for the Time function.

The improved performance (decrease in path cost errors) of only the LOEC participants within the off-nominal Time trial is surprising, particularly in conjunction with the opposite effect for the Exploration function. A similar trend (though not significant) was observed for the participants that had the combination visualization (both elevation contours and LOEC). There was no statistical difference in Time path cost errors across scenarios for the participants with elevation contours visualization. These differences in visualization were not seen in the Exploration case, where all participants performed the same.

There are a few reasons that all participants either did equally or better in the off-nominal condition for the Time cost function. First, this function was conceptually easier to understand as it depended on only two variables (one of them being slope) and hence, adaptation was possible. There might have been a learning effect also. Noteworthy are the post-questionnaire comments of the LOEC participants who mentioned leveraging the path elevation profiles[1] during the off-nominal trials. On the other hand, the participants with the elevation contours mostly used their visualization only. It may be that the more detailed information of the path elevation profile was a more useful aid for determining changes in path slope.

Another reason for the improved Time off-nominal performance of just the LOEC participants may be the effect of manual sensitivity analysis in the nominal phase of the experiment. These same participants had spent significantly more of their time modifying the Time paths, which may have led to some learning and fundamental understanding of how to optimize this cost function. Unfortunately, the participants with both LOEC and elevation contours visualizations did not significantly reduce their path cost errors for the Time off-nominal trial (though there was a

[1] See bottom of Figure 6.1.

decreasing trend). This may have occurred because participants within this visualization group had different strategies that either favored LOEC or elevation contours, as evidenced by the lack of participant preference for one visualization and post-questionnaires comments. By introducing two simultaneous visualizations in one group, the number of strategies was increased, making it difficult to compare effective strategies between the visualizations.

Finally, the Pareto front assessment revealed that the best off-nominal performers did not exclusively belong to the elevation contours group, but more of them were in the LOEC visualization group. This is counter-intuitive if it is assumed that participants solely depended on the visualizations to make their least-costly paths. It could be argued though that performance under degraded automation conditions depended on the amount of manual sensitivity analysis (amount of time spent modifying path) in the nominal condition, allowing participants to fundamentally understand the cost functions better. There was some evidence that LOEC participants did conduct more path modifications, which in turn would have assisted these participants in the off-nominal trials.

6.7 CONCLUSIONS FOR EXPERIMENT 2

In this experiment, four cost functions, three visualizations, and two scenarios types were examined for their effect on human-led path optimization. The cost functions tested were Distance, Time, Metabolic, and Exploration; each function depended on the previous, growing in number of variables and difficulty. The visualizations included elevation contours, levels of equal cost (LOEC), and a combination of both LOEC and elevation contour lines. Participants were tested in both nominal and degraded automation conditions.

Performance as defined by errors and time spent on task were driven by the cost function, though not necessarily the number of variables manipulated. The most complex cost function (the Exploration cost function which had the highest number of variables) was not completely understood by the participants. In this case, the levels of equal cost visualization helped participants initially make paths that were close to their optimal. Participants without the LOEC visualization did not know how to fundamentally optimize complex cost functions, like Metabolic and Exploration, and hence, implemented a "shortest path" heuristics.

On the other hand, the Time cost function was the most difficult cost function for participants to optimize even though it was relatively simple, depending on only two variables, Distance and slope. The results indicate that if a cost function is very sensitive to small changes in variables, like the Time function in this experiment, users could have difficulty in optimizing paths. These types of functions should be labeled as "overly-sensitive" cost functions in order to differentiate them from truly complex cost functions, Exploration. While Time was an "overly-sensitive" cost function, it is conceptually easier to comprehend than the Exploration function. Thus, under degraded automation conditions, participants were able to adequately adapt path planning strategies for the Time but not the Exploration cost function.

If considering the two main measures of performance in this experiment, path cost errors and time on task, the best performers under the nominal conditions were mostly in the elevations contours group. However, in the off-nominal cases, the LOEC participants emerge as being these better performers. The reasons behind this may be that while visualization did not have a main effect on performance, it did influence the choice of optimizing strategies. Participants with the additional LOEC visualization tended to spend more time modifying the Time function (as compared to users that just had elevation contours) which assisted them during degraded automation conditions. The levels of equal cost visualization, which aggregates all variables into one cost map, helped reduce the complex problem, in terms of providing an efficient optimizing strategy and promoted sensitivity analysis for difficult problems.

In terms of sensitivity analysis, participants could be categorized into two types: manual and "whole-path" sensitivity analysis. Manual sensitivity analysis, i.e., spending time modifying path solutions, was preferred by about three-fourths of the participants. Even though there was no difference in performance between these two strategies, there was a trend within the set of best performers which seemed to indicate that an increase in manual sensitivity analysis resulted in lower path cost errors.

In conclusion, for the task of path optimization, humans perform best when they leverage sensitivity analysis. While manual sensitivity analysis takes more time, it allows users to fundamentally understand how a path is optimized. As the presence of the LOEC visualization promoted sensitivity analysis, this visualization is a desirable attribute in decision support aids during the optimization of paths, particularly those that depend on "overly-sensitive" cost functions.

7 META-ANALYSIS, RECOMMENDATIONS AND CONTRIBUTIONS

7.1 LEVERAGING HUMAN-COMPUTER COLLABORATION

The research aims of this research were to investigate how to best leverage human-computer collaboration for the task of path planning and re-planning. This was accomplished by experimentally testing a prototype path planner with different degrees of automated data integration across varying task complexities. In all the experiments, there was a "what if" tool, which was allowed participants to always have the ability to manually change the paths. In the first experiment, automatic path generation and visualizations were assessed for their effect on human path planning performance. The three visualizations tested were 1) elevation contours, 2) levels of equal cost (LOEC) visualization, and 2) a combination of both. The LOEC visualization was an aggregate cost map. The task complexity was increased through the number of manipulated variables within the path cost function. In the second experiment, only one automation architecture was examined (manual path planning). This allowed for a better assessment of the role of sensitivity analysis for the task of path planning. Task complexity was further increased by introducing a degraded automation condition as well as more intricate cost functions. This scenario not only made the task more difficult, but also mimics a condition where human path planners must adapt to an underlying incorrect model or a limited resolution map. Based on the results of these experiments (described in Chapter 5 and 6), the following about leveraging human-computer collaboration is concluded.

In the first experiment, passive (or manual) and active levels of automation were compared across three different visualizations. In terms of human-computer collaboration, automated path segment generation (active automation) was helpful in decreasing the amount of time spent on the path planning task by 33% on average and virtually eliminated path cost errors. Unfortunately, when participants used the active automation, they chose not to utilize the manual sensitivity analysis ("what if") tool even though they had done so when manually creating paths (passive automation). This higher automation level and the lack of manual sensitivity analysis resulted in automation bias, and the penalty was decreased situation awareness, meaning participants were less aware of the elements and integration of these than when path planning with passive automation. Thus, while automated path generation was beneficial in reducing errors and time, it was detrimental with regards to situation awareness. In terms of visualization, there was no main effect present in this experiment, thus, situation awareness was not directly affected by the type of visualization. In high risk domains, human operator will have to react to unexpected circumstances and hence, must depend on their situation awareness. Thus, an acceptable trade-off between errors and situation awareness will have decided upon for any decision support system. Without the proper situation awareness, the chances of reacting appropriately in an emergency decrease due to limited knowledge-based reasoning capabilities.

In the second experiment only one automation architecture, passive automation, was tested which allowed different benefits of the visualizations to emerge. While there was no main effect due to visualization, the best performers, i.e., those that had low path cost errors and shorter task times, were typically found in the elevation contours visualization group. This was found only the case for the nominal cases, where participants could depend on the automation. Under degraded automation conditions, the participants with the LOEC visualization were more prominently represented in the set of best performers.

The LOEC visualization was also helpful for the most complex cost function, Exploration. Participants were able to leverage the LOEC visualization in order to initially create the Exploration least-costly path. When comparing the first and last paths costs (differential cost) for the nominal Exploration trial, participants with the LOEC were closer to an optimal solution on the first attempt. This would not be important if LOEC participants performed poorly, but there was no significant difference across visualizations. Therefore, while the Exploration function was a complex function, the LOEC visualization managed narrow down the problem space for participants.

In terms of sensitivity analysis, two types of strategies emerged among both experiments: manual and "whole-path" sensitivity analysis. In passive automation, both types of sensitivity analysis were observed among the participants, where 25% of the participants (in both experiments) used a "whole-path" sensitivity analysis strategy. During active automation (which was only present in the first experiment), most participants used a "whole-path" sensitivity analysis only. Thus, for this first experiment, three-fourths of participants switched from manual sensitivity analysis in passive automation to "whole-path" in the active automation. This switch was also accompanied by a decrease in situation awareness, implying that manual sensitivity analysis strategy is important for development of situation awareness.

It is important to address the difference between "whole-path" sensitivity analysis that occurred within active as opposed to passive automation. In active automation, whole paths were created after one waypoint was defined by the participant. In passive automation, whole paths were created after the participant defined all the waypoints. In essence, the type of sensitivity analysis was the same, however, in the passive, the user took a more important role in generating the path. Since situation awareness decreased for the active automation, the implication is that whole-path sensitivity analysis, where the human operator is more involved in the generation of path solutions, is more beneficial, or desirable, than one where the automation defines most of the path.

Within both experiments, there was no statistical difference between the sensitivity analysis types with respect to path cost errors. However, within the second experiment, there are some trends that seem to imply that there are benefits to conducting manual sensitivity analysis. Thus, it is hypothesized that human operators that conduct manual sensitivity analysis during path optimization are better able to adapt their optimization strategy to accommodate degraded automation condition. This was most prominent within the LOEC participants[1]. These participants tended to spend large portions of optimizing time conducting manual sensitivity analysis (i.e., larger percent time spent modifying) under nominal conditions. In conjunction, they performed better in the off-nominal conditions when compared to other participants. Specifically, LOEC participants decreased the path cost errors in the Time off-nominal path while the others showed no significant improvement. Additionally, LOEC participants were more present among the best performers in

[1] LOEC participants in the second experiment, as degraded automation conditions were only tested in this experiment.

the off-nominal trials. These results also imply that the presentation of the LOEC visualization promotes manual sensitivity analysis.

The question then becomes "Are there benefits directly related to the type of sensitivity analysis strategy?" To address this question, path planning performance between participants with different sensitivity analysis strategies were compared. Of the two main performance metrics (path cost errors and task times), cost error was selected as the appropriate evaluation metric because task time could bias the comparison since conducting path modifications is a more time-consuming strategy than creating new paths. In both experiments, there was no statistical difference with respect to path cost errors between the participants that chose manual waypoint as opposed to whole-path sensitivity analysis. However, in the Pareto front analysis for the second experiment (which included participants with both types of sensitivity analysis strategies), there was an apparent trade-off between path error and time. In general, an increase in task time led to a decrease in path cost errors, which was accompanied by an increase in percent time spent modifying path, as exemplified by the Pareto front participants for the nominal Time cost function (see section 6.5.1 and Figure 6.35).

This trend of improved path costs with an increase in path modifications prompted a meta-analysis that included participants in both experiments for all cost functions[1]. Within each cost function, participants were given a performance score based on the path cost errors (1 through 3, representing best, average, and worst performance) and ranked by the percent amount of time spent modifying paths (see Appendix C for details). Since it was already shown that no difference in path cost errors could be detected between sensitivity analysis types[2], the meta-analysis focused on only the participants that conducted manual sensitivity analysis. There was a significant moderate to low correlation between the performance score and amount of path modifications across both experiments (Spearman's rho = -0.19, $p = 0.008$). These results imply that more path modifications

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[1] Only for the passive automation condition from first experiment as only this automation architecture was tested in the second experiment.

[2] Additionally, there was no significant correlation between performance score and type of sensitivity analysis.

result in lower path cost errors. Thus, while conducting "whole-path" sensitivity analysis did not result in higher path cost errors when compared to manual sensitivity analysis, there was an increasing benefit to conducting more path modifications. The limitation to this benefit is the additional time it requires to conduct manual sensitivity analysis. Under time pressure, "whole-path" sensitivity analysis participants on average spent 1.4 minutes optimizing, while the other strategy took about twice as long.

While manual sensitivity analysis helped participants reduce path cost errors, the fact remains there were some cost functions that participants were poor at optimizing, namely the Time cost function and the Sun Score function. While it may be hypothesized that large Sun Score errors were due to participants not understanding how to optimize this function, the same can not assumed for the Time cost function. The Time cost function was highly sensitive to small path modifications. In other words, path changes resulted in large cost differences. To a certain extent, this was also observed for the Sun Score. Future investigation may want to consider how to further leverage active automation for "overly-sensitive" cost functions, such as developing a hybrid automated path generation where users defined many waypoints but the automation calculates the least costly path segments between these human-designated waypoints[1].

In summary, the key to a successful path planning and re-planning decision support system is to appropriately balance human and computer role allocation, such that humans conduct enough sensitivity analysis to maintain situation awareness. Manual sensitivity analysis is a time-consuming task, which might be appropriate during planning, but this strategy will have to be limited under re-planning time pressures. Based on this thesis research, knowledge-based reasoning is supported by manual sensitivity analysis, which was lacking when path were automatically generated for users. While leveraging automatic path generation results in better path performance (i.e., lower cost errors and shorter task times), the dependence on this aid leads to automation bias and decreased situation awareness. The missing components at the higher level of automation were time spent on the task and manual sensitivity analysis of the paths. Therefore, human operators should use aids that promote sensitivity analysis during the planning phase in order to best understand the relationship

[1] Currently, in the passive automation, the path segments between waypoints is a straight line.

between variables and path cost. Then, when confronted with the time pressured task of re-planning, he/she may leverage the knowledge gained from having already conducted the sensitivity analysis.

With respect to visualizations, the elevation contours representation promoted low cost paths with short task time when human operators could depend on the automation. However, the levels of equal cost (LOEC) visualization, which aggregated total path costs, helped participants initially create least-costly paths for the most complex cost function. Furthermore, LOEC visualizations appear to promote manual sensitivity analysis in the nominal case, which in turn was beneficial in the degraded automation condition, where low path errors and time was observed for participants with this visualization. Finally, two types of sensitivity analysis strategies were observed, one that leveraged the available "what if" tools for waypoint modification and the other that created whole paths. While there was no difference in performance across the strategies (i.e., both sensitivity analysis strategies were equally effective), the increased use of the manual waypoint sensitivity analysis (i.e., path modifications) led to decreased path cost errors.

7.2 DESIGN RECOMMENDATIONS

7.2.1 PATH PLANNING AND RE-PLANNING DECISION SUPPORT AIDS

Based on the work domain analysis and the analysis of the experiments conducted, the following design recommendations for decision support aids that support both planning and re-planning of paths are suggested. These recommendations are generalized beyond space application (i.e., real-time aids for human planetary exploration), and can be applied to any complex decision support systems that assists operators in the tasks of path planning and re-planning within other domains, such as UAV operations, search and rescue robots, and ground soldiers. The recommendations specific to planetary EVA are discussed in a subsequent section.

The results of the experiments conducted in this thesis indicate a positive relationship between manual sensitivity analysis with both situation awareness and performance under degraded automation conditions. Thus, the first design recommendation is:

* **Provide "what if" tools for path planning and re-planning in order to encourage sensitivity analysis.** A "what if" tool was essential for manual sensitivity analysis and thus, such a tool within an automated aid will help operators find alternative routes and plans when faced with re-planning. Sensitivity analysis, for both planning and re-planning, should be encouraged as it was shown to possibly lead to lower path costs. In the PATH test bed, the basic "what if" tool included moving, adding, and deleting of waypoints, and path cost changes were only visible once a modification was executed. Further manual sensitivity analysis tools may be beneficial (see also 7.3).

With respect to visualization, there was no main effect due to this test condition. However, there are visualization recommendations based on the observed trends for the experiments conducted:

* **Make aggregate cost information available to human operator through direct perception visualizations.** With the levels of equal cost visualization (LOEC), human operators are leveraging direct perception, which "pushes" a complex problem solving task to a lower level of cognitive control. The LOEC visualization, which aggregates multivariate data, was particularly useful for complex cost functions and helped to visualize high cost areas. Hence, the path planner may want to take advantage of this visualization under time pressure to create new paths. Additionally, LOEC users tended to conduct more sensitivity analysis. Thus, if providing an aid like the LOEC visualization during pre-planning and training, the human operator will likely develop more accurate mental models of how the cost functions interact with important variables (for instance, terrain characteristics for the planetary EVA application), allowing for better adaptation to imperfect automation.

* **Make raw (or basic) information available to the human operator.** When the decision support aid's automation models are incomplete (e.g., low map fidelity), the operator needs to have access to the most basic of data (which is domain specific) to adapt their new paths and accommodate for discrepancies. In this thesis investigation, the raw data was terrain models, and best performance under nominal conditions were observed with this basic information visualization (elevation contours). Providing access and the choice to both basic

and aggregate information is important to support both nominal and off-nominal path planning conditions, however, overlaying them was not beneficial.

The work domain analysis (WDA) conducted for this research examined planetary EVAs. However, there are some broader implications for this analysis as it was one that included and assessed why and how paths were re-planned. Hence, the WDA, in conjunction with the results of the experiment, suggest the following design recommendations:

- **A human operator should be involved in both the path planning and execution phases of the path.** In order for re-planning to be effective, the human operator should be knowledgeable about how the path was planned. He/she will then be familiar with the cost functions and reasoning behind the path selection. This may be accomplished in the planning phase, where operators may leisurely conduct an extensive manual sensitivity analysis of path solutions. If the human agent has a more complete understanding of the plan, upon path execution (e.g., actually traversing or operating some robotic agent along that path), he/she will be more aware of deviations from the plan. Furthermore, understanding how deviations occurred, e.g., identifying erroneous cost functions, is essential for re-planning new path solutions.

- **The path planning aid should be flexible.** Though not directly tested in the PATH experiments, the work domain analysis indicated that re-planning revolves around assessing the different options available. This can only be accomplished by providing a flexible aid for path planners. In general, this corresponds to providing the human operator the ability to add new or remove constraints (e.g., physical terrain obstacles) and modify cost function models. Specifically for the domain of planetary exploration, other automated function include changing the cost function models based on type of transportation modality (e.g., walking vs. driving) and reprioritization of sites or waypoints along the path.

The above design recommendations can be applied to a variety of domains that require human operators to path plan and re-plan, including transportation domains. In these circumstances, the domain is complex, requiring the operator to manipulate multiple variables, sometimes having to re-plan under time pressure. Therefore, the same lessons learned from this investigation (e.g., the importance of sensitivity analysis, the use of display visualizations, and the need for flexibility of automated aid) may help operators in their routing tasks and in dealing with unexpected future events or imperfect automation.

In terms of the most common, commercial path planning aids, such as automobile GPS and on-line path planners, these recommendations are still relevant but should be interpreted more broadly. Most on-line path planners find shortest or fastest routes between two locations, and provide users some ability to constrain paths, like avoiding tolls or highways. The more sophisticated planners allow users to organize trips with multiple intermediate waypoints, while the planner automatically finds routes in between. Automobile planners (and up-and-coming mobile GPS systems) have become highly automatic, planning routes and directing drivers to their destination. Like on-line planners, paths are optimized based on time or distance. Real-time updates allow car navigation systems to revise paths, avoiding traffic and leading users to the cheapest gas station or the closest rest stop. Additionally, theses systems can find alternative paths and re-route drivers if they deviate from path (or can be triggered by user).

Unfortunately, neither of these planners, on-line or automobile, permit users to modify the actual path itself (i.e., adjust multiple paths segments). In addition, if automobile planners follow the on-line trend, they will start multi-waypoint path planning, and hence, increase the amount of user interactivity. Both of these system could introduce improvements at the planning phase, particularly giving users the ability to modify paths. Integrated "what if" tools (similar to those developed for PATH) would help users create paths that suit their preferences and assess the cost (in terms of distance and time) of their modifications. Furthermore, visualizations (analogous to LOEC) could assist users in the path planning phase by highlighting areas which users prefer, like scenic areas, or want to avoid, like construction zones. During the planning phase, users may become familiar with the pros and cons of particular routes, saving some and selecting one. If re-planning is required, the user could revert to one of the previously created paths that better suits his/her needs. Thus, while the set of design recommendations apply more directly to complex, time-pressured domains, beyond planetary EVAs, they can be considered in a broader context and lessons learned are relevant to automated planners used daily.

7.2.2 FUTURE REAL-TIME PLANETARY DECISION SUPPORT AIDS

The investigation of this thesis focused on understanding how human-automation collaboration can be leveraged for the geospatial problem solving task of path planning. Such an automated path planner would only be part of a larger, more sophisticated computer tool for future astronauts exploring the Moon or Mars. In addition to the already discussed design recommendations, the following requirements are proposed specifically for real-time planetary decision support aids.

- **Functional requirements:**
  - The real-time decision support aid should assist astronauts or mission controllers in determining if re-planning is needed. Thus, the aid must present to the human operator actual and expected path costs along the traversal.
  - Real-time tracking of the position of the astronaut and other costs, such as energy consumed, is required. Position (and potentially orientation) tracking should be overlaid with the planned path, though this depends on the navigation system in place on the planetary surface.
  - Automatic assessment of variables that are responsible for deviations from planned path. For instance, if the source of errors is terrain-specific, path costs deviations can be correlated to terrain characteristics in order to determine the true relationship between cost and terrain (i.e., correct cost model).
- **Information requirements:**
  - A complete real-time decision support aid should have access to all the inputs and constraints listed in the Planetary EVA Framework (Chapter 3). These inputs and constraints do not need to be presented to the astronaut or mission controller at all times. However, human operators must have access to this information if it is required for path re-planning.

- The decision support aid should have a terrain map (both an aerial map and a digital elevation model, i.e., elevation information) with an overlay of the planned EVA.

- The pertinent associated path costs must be included with the path itself. The costs (already identified in the Chapter 3) include for instance, energy consumed. The EVA schedule is also an essential to display alongside the path.

- Path re-planning is likely to be triggered by incomplete cost function models or poor map resolution. Providing the astronaut with a sense of the level of uncertainty would be beneficial (e.g., map resolution or confidence intervals of path costs).

7.2.2.1 HARDWARE IMPLICATIONS

The information needed for path planning and re-planning can be displayed on any type of computer screen. There are several options that have been previously suggested for use by astronauts during EVAs: heads-up display (HUD), a spacesuit-imbedded screen, or a separate computer display (Figure 7.1). HUDs and wearable computers are feasible but may interfere with the astronaut's field of view (already encumbered with wearing a helmet). Hence, a screen imbedded or attached to the spacesuit arm or a small, portable computer is another option.

Figure 7.1 Future NASA concepts of information systems. From left to right: heads-up displays (image s99_04197), spacesuit imbedded screen (image jsc2004e18850), separate computer screen (image jsc2004e18859).

Above all, astronauts (or mission controllers) must be able to interact with the map and re-planning aid, and be able to conduct a sensitivity analysis on planned paths in order to decrease path costs and maintain situation awareness, critical for knowledge-based reasoning. However, these requirements have associated hardware implications with respect to input devices. High levels of human-computer interaction for re-planning make buttons and voice commands inadequate as they are poor methods for communicating geospatial information. Thus, the physical implementation of re-planning decision support aids requires input devices akin to a computer mouse (i.e., pointing, clicking, and dragging on a screen). Unfortunately, current pressurized spacesuit technology limits hand dexterity, which restricts the use of the traditional computer mouse. If the decision aid were on a portable computer, a track ball could be used for pointing and dragging (with the addition of a button used with the other hand). If an imbedded screen were to be implemented (such as in Figure 7.1), a trackball is unlikely to be used. Alternatively, it could be feasible to integrate a stylus-type device on to the tip of a gloved finger to point and drag on the touch screen; a button could be incorporated on the other hand or finger. This would also promote direct manipulation of information on a screen, be it on a portable computer or on the spacesuit arm.

7.3 Possible Future Research

The following is a list of potential improvements for PATH and possible new research directions based on the experimental results of this thesis.

- **PATH improvements**: PATH was purposefully designed to be a relatively simple path planner (in order to conduct controlled experimentation). The improvements mentioned below are based on observation and include the comments from participants.

    - Normalize path costs relative to one path. This would help users compare costs between paths more easily and consequently, the bar cost graph would depict the path cost differences. Potentially, this may increase the user's ability to differentiate between small path cost differences.

- Provide to the user a sense of how much each variables or cost functions is contributing to the overall path cost. This can be accomplished simply through a pie chart or stacked bar graph which reflected the percent each variable contributes.

- Provide larger map and/or zooming capability for the map. This improvement may affect the total task time (as it is an additional functionality that users may abuse) while not affecting path cost errors, yet it may provide the user the ability to make smaller resolution changes. Similarly, path cost and elevation profiles may be enlarged.

- Prevent or assist users from making paths that cross obstacles. Participants were not permitted to make paths that included an obstacle, and thus were required to restart the paths if they mistakenly intersected one. The planner could automatically fix the user's path and avoid obstacles.

- **Provide additional "what if" tools**. Other aids that may assist in sensitivity analysis are: 1) an "undo" modification button, which would allow users to return to previous path, 2) a "copy" path button, 3) a "save" path button and 4) a log and upload capability of saved paths with corresponding costs. These improvements are relatively simple compared to the often requested functionality of real-time updating of path cost changes while simultaneously modifying path. This dynamic version of path modifications could potentially facilitate manual sensitivity analysis.

- **LOEC improvements and research opportunities**:

  - Change color gradient used for LOEC visualization. The yellow-purple color combination was selected in PATH's design because it did not overlap with the path colors while still providing the range of colors for the user to differentiate between. The color differences can be made more apparent to the user by implementing a non-linear color gradient (currently, it is linear). This would have the effect of making relatively high cost areas more purple. If the path color constraint is removed, there are other methods of improving the color differences, such as choosing more colors (for instance, a rainbow set) and providing the user with a dynamic slider (i.e., making the user select the set of colors he/she was to visualize). These changes would need to be tested against the present LOEC visualization in order to determine if these improve upon the current design.

  - Make LOEC visualization a dynamic aid. Currently, the LOEC visualization is static as there is only one goal. However, a dynamic version of the LOEC visualization may be implemented. One way to do this is by permitting the user to drag the goal location on the map while the automation calculates and presents the new LOEC (for the new goal), giving the user the ability to assess relative costs between intermediate waypoints and allow him/her to observe how the LOEC visualization changes as it is moved around the map. This would be particularly useful if users were tasked to create paths that traverse many critical way-areas. The second way to implement a dynamic LOEC visualization is by giving the user the ability to change the cost function (variables or relationships) and observe how the visualization itself changes based on the cost function modifications. Additionally, by making LOEC a dynamic visualization, it could be considered a type of sensitivity analysis aid. Such an improvement on the LOEC visualization would be computationally expensive, and thus some preliminary studies should assess both the potential advantages over a static LOEC, implications of modifying cost functions models on overall path planning performance, and the ease of use of such an aid.

- **Trade-off between active automation and situation awareness**: This thesis investigated one implementation of active automation, where the user selected only one waypoint between a given start & goal and the automation plotted the least costly, in-between path segments. Other active automation implementations (more appropriately named hybrid automation) could require users to select multiple waypoints whereas the automation fills the least costly path segments between these. This would increase the amount of the path that is user defined. Future research may examine if this method of leveraging automation encourages users to conduct more manual sensitivity analysis and to maintain situation awareness while keeping path cost errors small and short task times.

- **Utilizing PATH as a strategic planner**: Presently, PATH is designed as a tactical planner, meaning it is to be used for planning paths based on current, pre-determined conditions (e.g., start, goal, and sun position). A strategic planner would imply that these conditions could be set and changed to reflect future scenarios. A potential new research direction with PATH could be to assess the effectiveness of PATH as a strategic planner, the required "what if" tools to facilitate this type of planning, and to further understand the operator's capability to conduct these types of searches.

- **Modify PATH for real-time path re-planning**: Even though PATH is a planning aid, it can be modified to conduct real-time path re-planning. This could be accomplished by simulating events that require the user's to re-plan. Furthermore, PATH could be adapted for Earth conditions (e.g., local terrain map) and used in real-time to re-plan traverses.

7.4 CONTRIBUTIONS

The aim of this research was to enable knowledge-based reasoning for geo-spatial path planning problem through both visualization and human-automation interaction. In order to explore this problem, different human-automation role allocations were examined and tested in order to understand how humans conduct complex optimizations under different automated assistance levels in a geospatial task. As a result, this thesis begins to fill in a critical interdisciplinary research gap between human interaction and artificial intelligence by examining how automation impacts path planning performance. While focused on human planetary exploration, in part due to the recent national attention on space exploration and humans returning to the Moon, the acquired knowledge for human interaction with automation planners applies to a many other domains such as air traffic control, robotic exploration, and rescue on, above, and below the Earth. Furthermore, the results of this thesis could be of particular interest to industry as automated planners are being integrated in a myriad of commercially-available technologies.

This thesis has provided the following contributions:

- A framework for human-robotic planetary EVA planning, including key input variables, constraints, and outputs in the form of information requirements (Chapter 3). This framework is broad enough that it can be adapted to other human-robotic planning domains.

- A prototype path planner based on lunar terrain models and planetary cost functions (Chapter 4). While this planner does not incorporate all the Planetary EVA Framework elements, it focuses on fundamental pieces, the planned path, different visualizations, and increasingly complex cost functions. Thus, it can be the basis of a more complete, future planner.

- Quantification of path planning performance across different decision support visualizations, cost function complexity, automated path generation, and degraded automation condition (Chapters 5 and 6). It is concluded that sensitivity analysis is key to maintaining situation awareness and improving path planning performance, though the benefits are limited to the amount of time available to conduct path modifications. The levels of equal cost visualization did not have a direct effect on performance, but it may encourage sensitivity analysis, which was necessary for adequate performance for users under the degraded automation condition.

- Identification of cognitive strategies people use when interacting with automated path planners, which has not been addressed in previous research.

- Design recommendations for future real-time decisions support aids for planetary EVAs, including information, functional, and hardware implications.

Planetary exploration is a reality with rovers on Mars. These robotic agents are the eyes and legs of the scientists on Earth. If we are to send humans back to the Moon in just over a decade, and move on to Mars from there, we need to focus attention towards the technologies supporting people on other planetary surfaces as these technologies maintain humans' safety in these extreme environments. Human-system integration is the key to the success of any mission that includes both humans and robotic agents, and this research concentrated on developing robust decision support systems for EVAs to ensure safe and productive missions.

APPENDIX A: SUPPLEMENTARY INFORMATION FOR EXPERIMENT 1

PILOT EXPERIMENT IMPLICATIONS

Before the first experiment was undertaken, a pilot experiment was conducted. The pilot revealed several issues in the experimental methods that were subsequently addressed. Participants were divided into one of three groups: 1) manual path planning with an elevation contours map, 2) manual path planning with the option of using the levels of equal cost (LOEC) visualization and elevation contours maps, and 3) automatic path planner with elevation contours map (highest level of automation). Since participants in the second group were allowed to change the map visualization they were provided, they were able to opt-out from using the LOEC visualization. This problem was fixed by eliminating the option to choose map visualizations.

Additionally, participants in the third group only had to request the automatic path planner for the least-costly path, resulting in experimental bias; the path planning task was too easy for these participants. This problem was fixed in the first experiment by changing how the automatic path planner functioned. Instead of providing a least-costly path from the given start and goal locations, the user determines an intermediate waypoint and the automatic planner only finds least-costly paths from the start to the intermediate waypoint and from there, to the goal. The user's waypoint is constrained to be within a given critical way-area. The critical way-areas were designed to always include the least-costly path from the given start and goal locations.

An analysis of cost function presentation order (i.e., which cost function was seen first) revealed a learning effect, and that counterbalancing did not work as expected. The effect detected was that participants who did the hard and then easy cost functions performed better than the participants who did the easy and then hard cost functions. Thus, in order to equalize the learning effect, only one order is implemented. Finally, the selected trials varied in difficulty, which prevented accurate performance comparisons. More emphasis was thus placed on selecting trials to ensure equal difficulty across conditions.

PRE-QUESTIONNAIRE

A brief pre-questionnaire was given to the participants before they started the experiment. The information gathered was used to balance the visualization groups and to test (and control) for participant experience which may have affected path planning performance.

Subject number: ________ Group number:________

Age: ________ Gender: male/female Color blindness: yes/no

Occupation: graduate student/undergraduate/staff/faculty/unaffiliated

Major: ________

How often do you play video games?

Never/Less than 1 hour per week/Between 1 and 4 hours per week/ Between 1 and 2 hours per day/More than 2 hours per day.

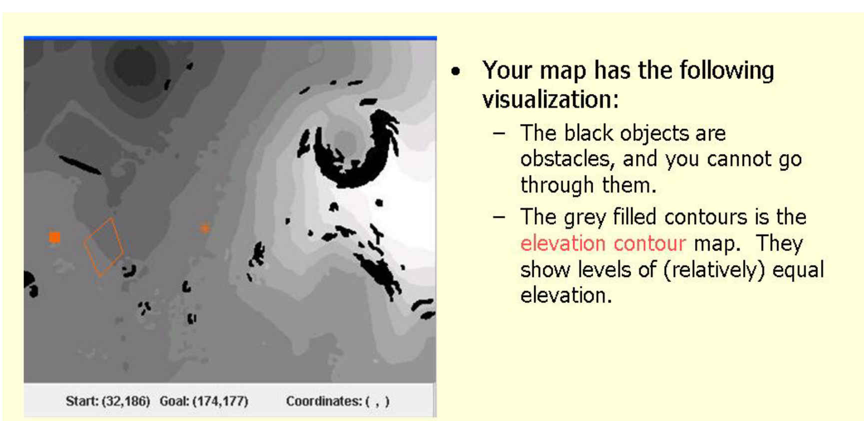
Please mark the skills you feel proficient in:

Orienting a map/Triangulating position/Estimating distance on map/ Interpreting topological map/Off-trial hiking.

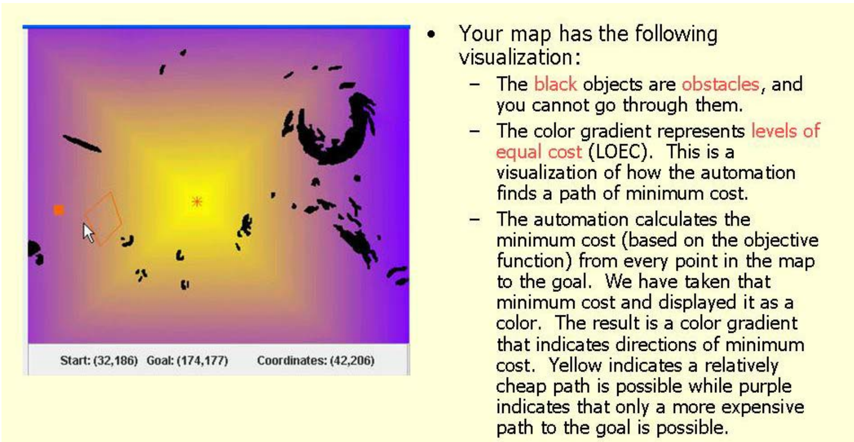
VISUALIZATION DESCRIPTION

Each subject was given the description of the visualization he/she would be using during the experiment. Subjects read only the descriptions (shown below) for their own particular visualization, and no further instructions were provided.

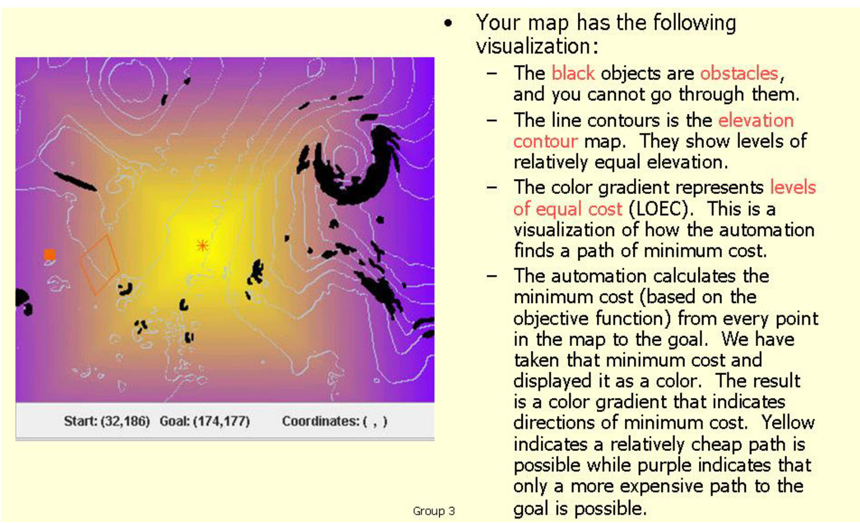
Description given to subjects for the elevation contours visualization:



Description given to subjects for the levels of equal cost (LOEC) visualization:



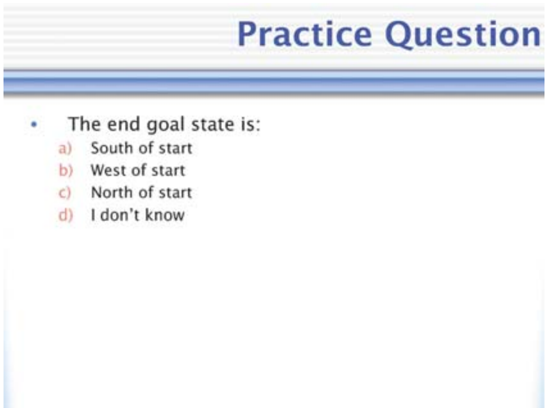
Description given to subjects for the LOEC and elevation contours visualization:



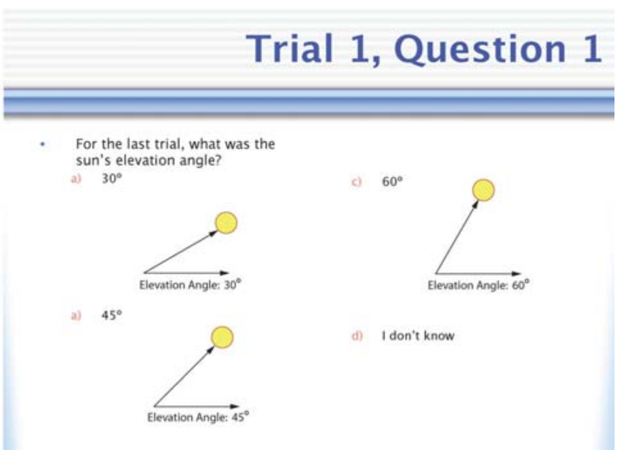
SITUATION AWARENESS QUESTIONS

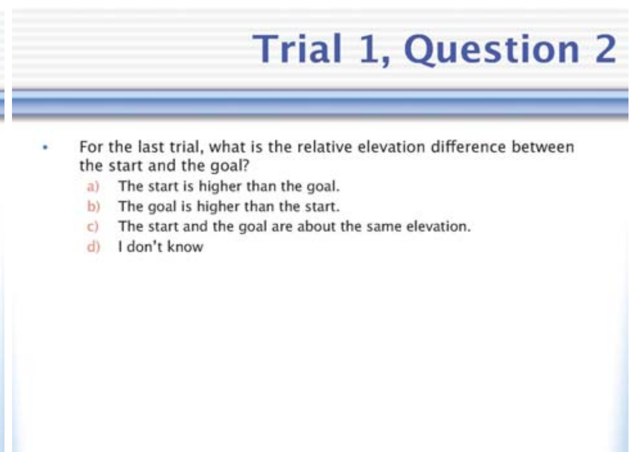
The situation awareness (SA) questions were designed to address SA levels 1 and 2. SA level 1 focuses on the perception of elements, while level 2 is about the integration and comprehension of these elements. Therefore, the SA questions (asked after each trial) specifically test participants on their perception of elements about the previously tested trial, such as sun position or obstacles that had to be avoided, and their integration and comprehension about how these elements affect path costs. The SA questions are shown below as presented to the participants, and include the corresponding SA level the question targets.

Practice Question (SA level 1)

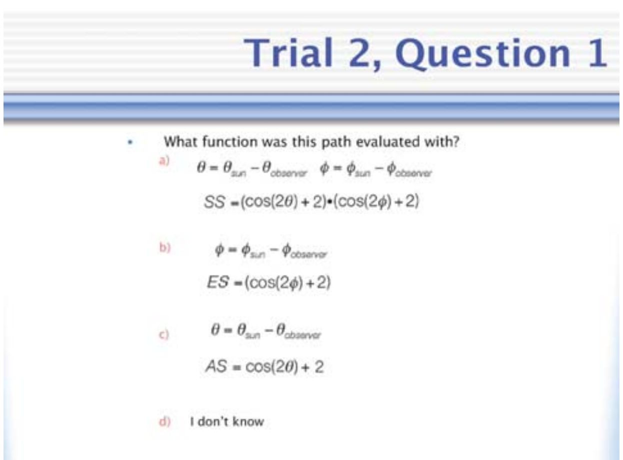


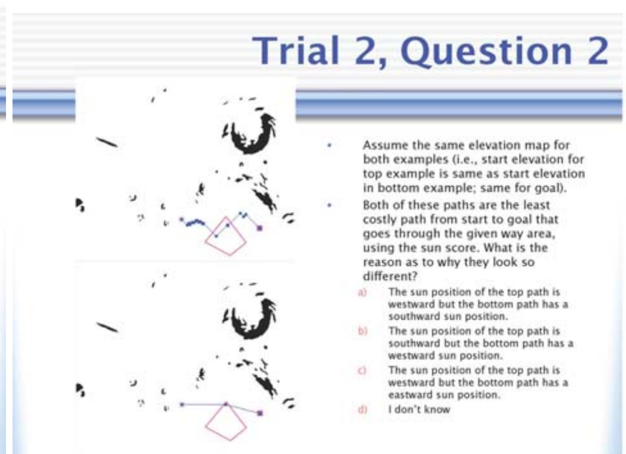
Trial 1: Question 1 (SA level 1) & Question 2 (SA level 2)



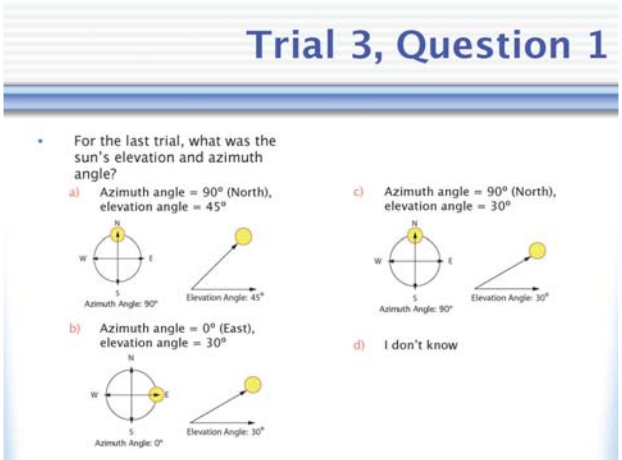


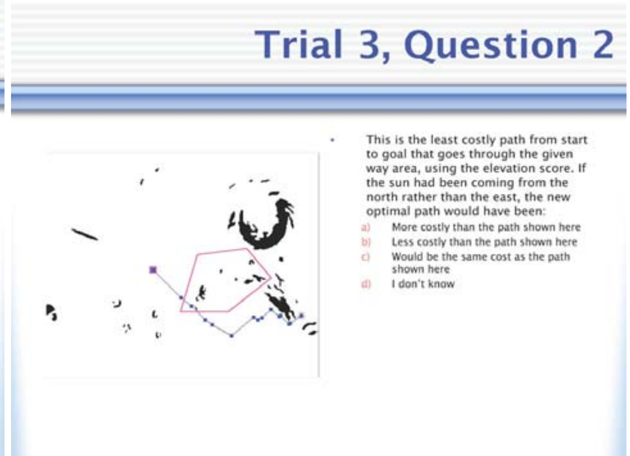
Trial 2: Question 1 (SA level 1) & Question 2 (SA level 2)



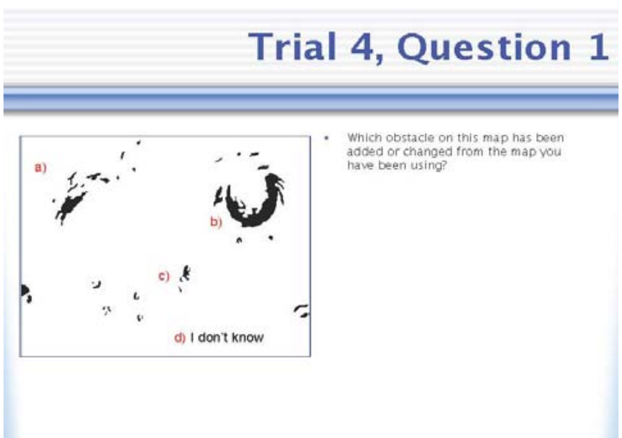


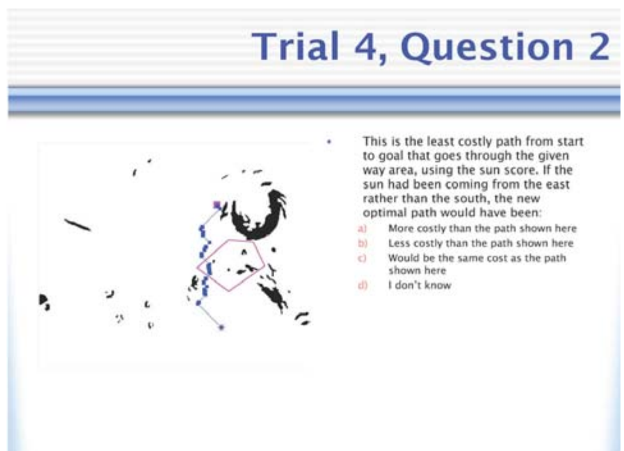
Trial 3: Question 1 (SA level 1) & Question 2 (SA level 2)





Trial 4: Question 1 (SA level 1) & Question 2 (SA level 2)



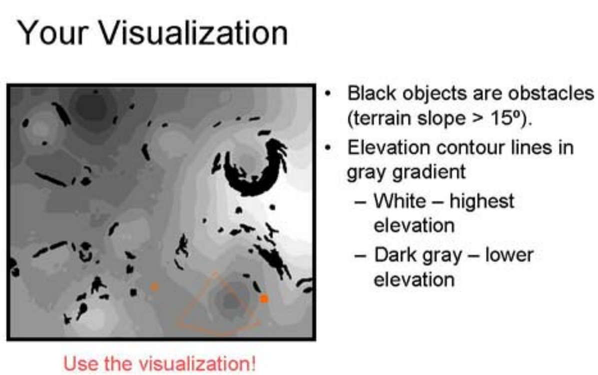


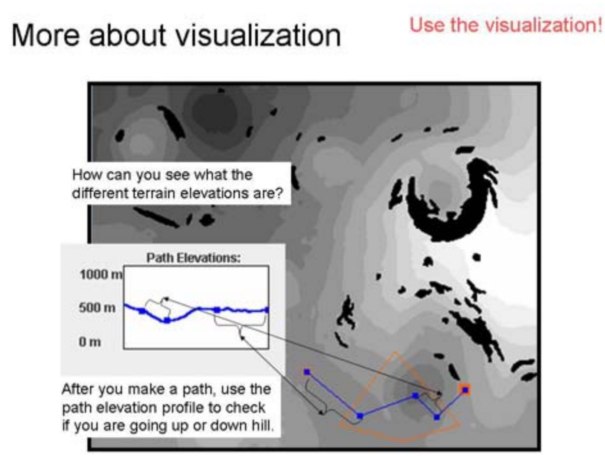
APPENDIX B: SUPPLEMENTARY INFORMATION FOR EXPERIMENT 2

VISUALIZATION DESCRIPTION

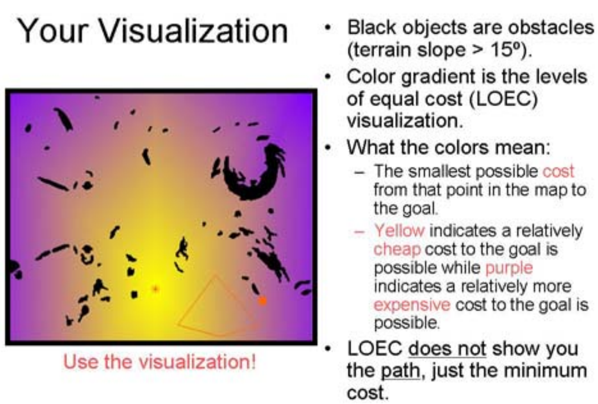
Similar to the first experiment, each subject was given the description of the visualization he/she would be using during the experiment. Subjects read only the descriptions (shown below) for their own particular visualization, and no further instructions were provided. These descriptions are more detailed than those in the first experiment because participants had commented (during the de-brief) that they would have preferred more explanation about the visualization (particularly those participants with the levels of equal cost visualization).

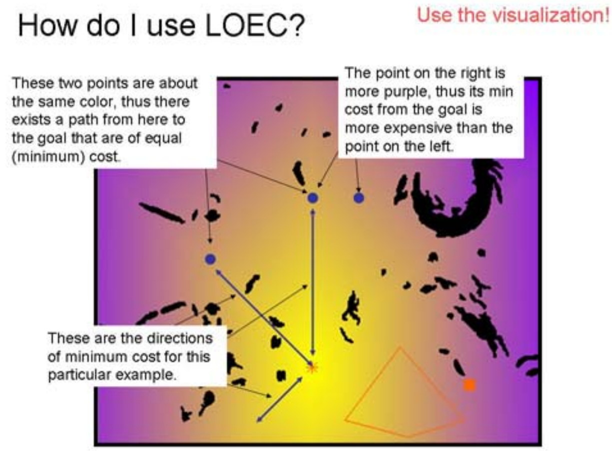
Description given to subjects for elevation contours visualization:

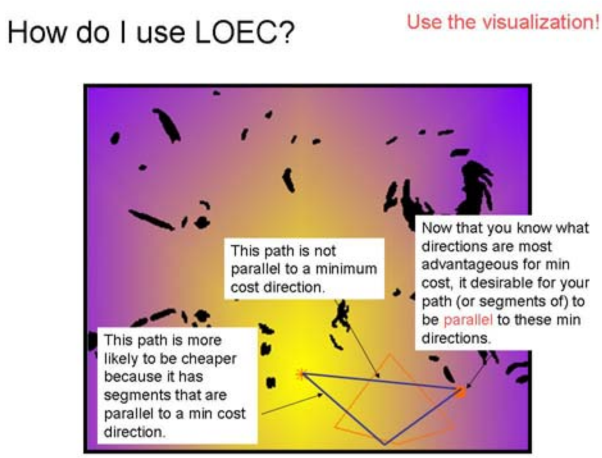


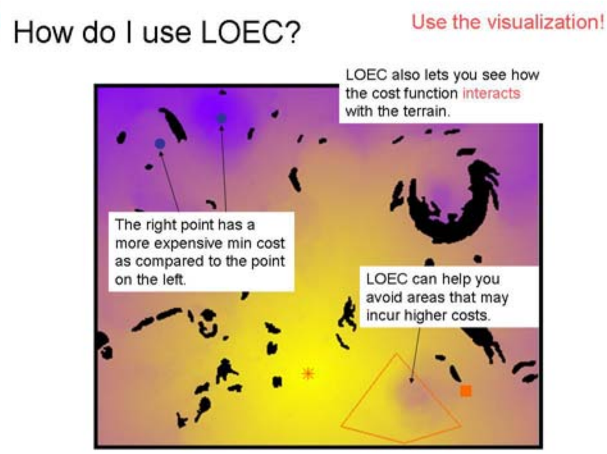


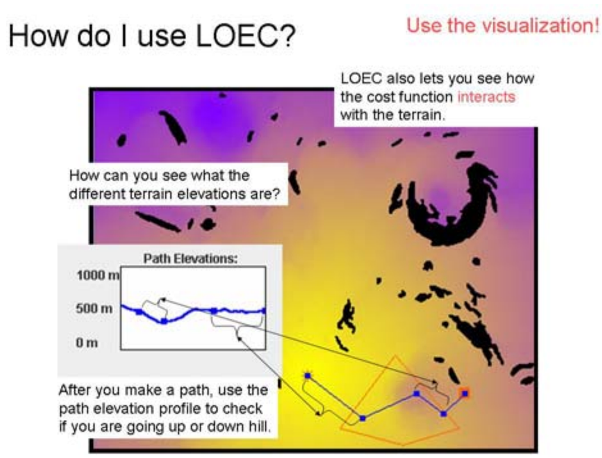
Description given to subjects for the levels of equal cost (LOEC) visualization:



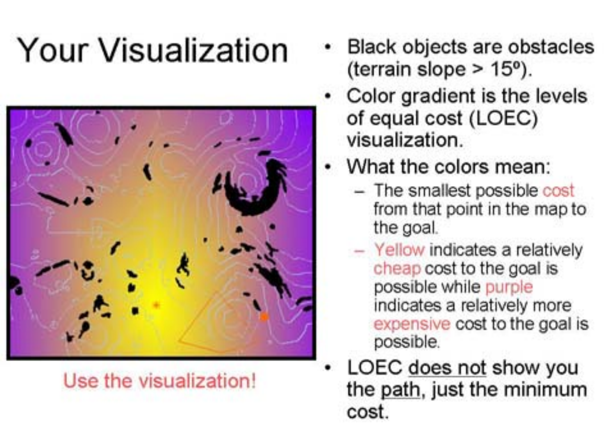


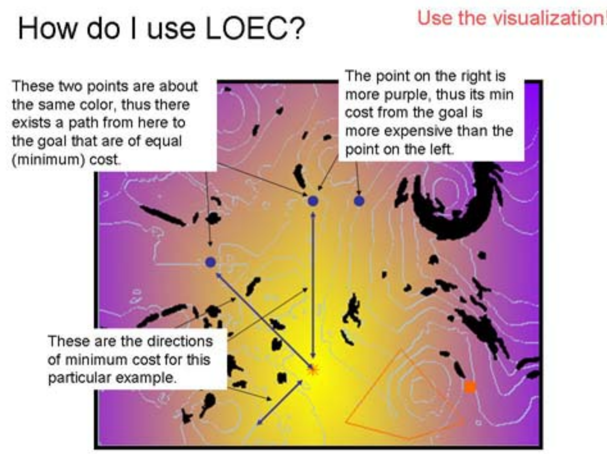


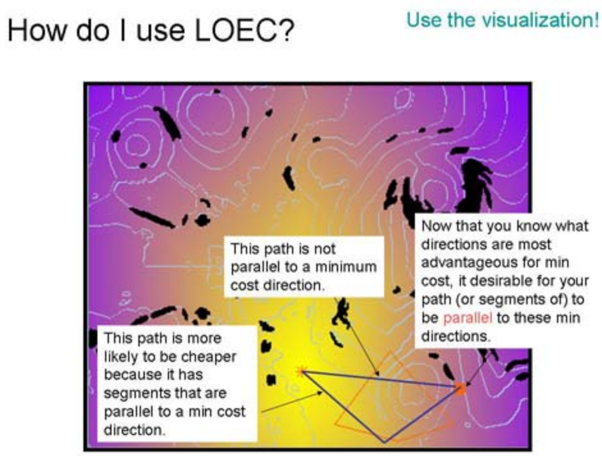


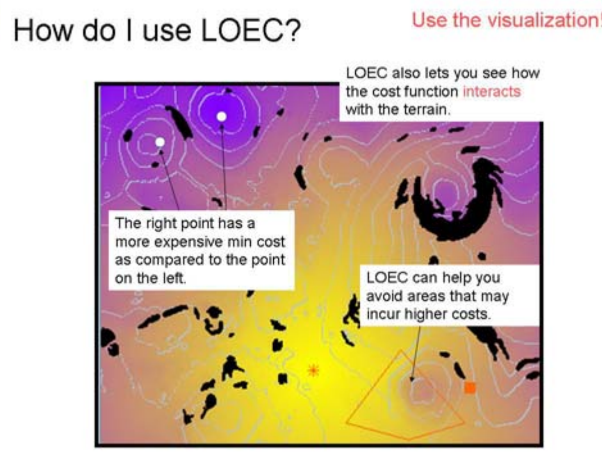


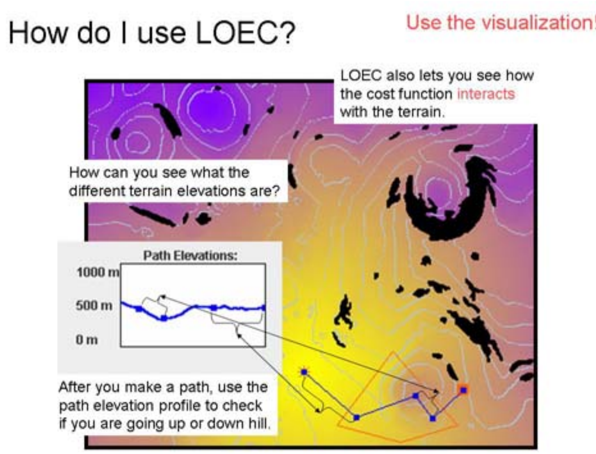
Description given to subjects for LOEC and elevation contours visualization:











ASSESSMENT OF COVARIATES

Before the experiment was conducted, each participant completed a map planning test (with corresponding score) and self-rated experience with hiking and map-use. These two metrics were correlated to the two main dependent measures, path cost errors and time penalty, in order to determine if they were significant covariates.

Map planning test scores were tested for correlation to path cost error and time penalty for each of the 6 tested conditions (4 nominal, 2 off-nominal trials). There were no significant correlations between scores and path cost errors, or with time penalties. Even though visualization groups were not balanced for map score, there was no significant difference between the groups with respect to scores (Kruskal-Wallis test, $\chi^2(2, N = 34) = 0.42$, $p = 0.81$). Thus, scores were not used as a covariate in the analysis.

Spearman's rho correlation results between map planning test scores and path cost error

Map planning test score	Nominal Scenarios				Off-nominal Scenario	
	Distance	Time	Metabolic	Exploration	Time	Exploration
Correlation coefficient	0.11	-0.14	0.15	-0.01	0.04	0.06
p-value (2-tailed)	0.54	0.43	0.40	0.96	0.81	0.73

Spearman's rho correlation results between map planning test scores and time penalty

Map planning test score	Nominal Scenarios				Off-nominal Scenario	
	Distance	Time	Metabolic	Exploration	Time	Exploration
Correlation coefficient	-0.15	-0.03	-0.16	-0.18	-0.10	-0.20
p-value (2-tailed)	0.40	0.87	0.36	0.31	0.57	0.27

The original map & hiking experience 5-point scale permitted participants to self-rate how much familiarity they had with hiking and/or using topographic maps in their traverses. Only one participant self-rated as having neither hiking nor map use experience. In order to correlate experience with path cost errors and time penalty, the categories were rearranged to four bins: 1) little/no map experience, 2) some hiking experience, 3) intermediate experience hiking with maps, and 4) expert hiking with maps. The visualization groups were not balanced for experience and no significant difference between visualization groups was detected (Kruskal-Wallis test, $\chi^2(2, N = 34) = 0.52$, $p = 0.77$).

With respect to experience and performance correlations, there were no significant correlations between the experience and path cost errors, or with time penalties. There was only a marginally significant correlation between time penalty and experience within the Distance cost function trial. For all the other conditions, this trend was not significant (and smaller in effect size). Thus, experience was not used as a covariate in the analysis.

Spearman's rho correlation results between map & hike experience and path cost error

Map & hike experience	Nominal Scenarios				Off-nominal Scenario	
	Distance	Time	Metabolic	Exploration	Time	Exploration
Correlation coefficient	0.03	-0.12	-0.13	-0.12	0.25	0.08
p-value (2-tailed)	0.86	0.49	0.48	0.51	0.15	0.66

Spearman's rho correlation results between map & hike experience and time penalty

Map & hike experience	Nominal Scenarios				Off-nominal Scenario	
	Distance	Time	Metabolic	Exploration	Time	Exploration
Correlation coefficient	-0.30	-0.16	-0.08	0.01	-0.21	-0.07
p-value (2-tailed)	0.08	0.39	0.65	0.97	0.24	0.72

PATH COST ERRORS

Descriptive statistics for path cost errors within visualizations

Visualization Group	Nominal			Off-nominal		
	Distance	Time	Metabolic	Exploration	Time	Exploration
Elevation contours	1.04 ± 0.04	1.54 ± 0.17	1.07 ± 0.02	1.05 ± 0.01	1.58 ± 0.22	1.11 ± 0.03
LOEC	1.03 ± 0.03	1.63 ± 0.14	1.08 ± 0.03	1.07 ± 0.02	1.47 ± 0.16	1.10 ± 0.03
Both visualizations	1.02 ± 0.02	1.64 ± 0.10	1.06 ± 0.02	1.06 ± 0.02	1.53 ± 0.20	1.10 ± 0.04
Total	1.03 ± 0.03	1.60 ± 0.14	1.07 ± 0.02	1.06 ± 0.02	1.53 ± 0.20	1.10 ± 0.03

- In Phase 1, there was a significant difference in path cost errors between cost functions (Friedman test: $\chi^2(3, N = 32) = 72.56, p < 0.001$).

Wilcoxon Sign tests results for comparisons between cost functions, Phase 1

NOMINAL	Time	Metabolic	Exploration
Distance	Z = -5.01, p < 0.0001	Z =-4.11, p <0.0001	Z =-3.99, p <0.0001
Time		Z =-5.01, p <0.0001	Z =-5.09, p <0.0001
Metabolic			Z = -0.74, p = 0.46

Kruskal-Wallis test results for path cost errors differences between visualization groups within cost function

Cost Function	Scenario	Kruskal-Wallis, χ^2	p-value
Distance	Nominal	$\chi^2(2,33) = 0.67$	$p = 0.72$
Time	Nominal	$\chi^2(2,34) = 2.25$	$p = 0.33$
Metabolic	Nominal	$\chi^2(2,33) = 2.33$	$p = 0.31$
Exploration	Nominal	$\chi^2(2,34) = 3.94$	$p = 0.14$
Time	Off-nominal	$\chi^2(2,34) = 1.83$	$p = 0.40$
Exploration	Off-nominal	$\chi^2(2,34) = 0.06$	$p = 0.97$

Wilcoxon Sign test results for path cost errors differences between cost functions

Cost Function Comparisons	Wilcoxon Sign test & p-value			
	Regardless of visualization	Elevation contours	LOEC	Both visualizations
Time off-nominal – Exploration off-nominal	$Z = -5.09$, $p < 0.0001$			
Time nominal – Time off-nominal	$Z = -1.96$, $p = 0.05$	$Z = -0.39$, $p = 0.70$	$Z = -2.22$, $p = 0.026$	$Z = -1.60$, $p = 0.11$
Exploration nominal – Exploration off-nominal	$Z = -4.86$, $p < 0.0001$	$Z = -3.06$, $p = 0.002$	$Z = -2.93$, $p = 0.003$	$Z = -2.58$, $p = 0.01$

TOTAL TIME: TIME PENALTY

Descriptive statistics for time penalty

Visualization Group	Nominal				Off-nominal	
	Distance	Time	Metabolic	Exploration	Time	Exploration
Elevation contours	1.69 ± 0.30	2.16 ± 0.93	1.78 ± 0.42	2.01 ± 0.62	2.00 ± 0.77	1.84 ± 0.55
LOEC	2.06 ± 0.53	2.28 ± 0.80	2.07 ± 0.56	1.89 ± 0.49	2.38 ± 0.94	1.84 ± 0.64
Both visualizations	1.84 ± 0.40	2.49 ± 1.16	1.93 ± 0.70	2.08 ± 0.69	2.17 ± 0.66	2.12 ± 0.80
Total	1.82 ± 0.40	2.30 ± 0.95	1.94 ± 0.57	1.99 ± 0.59	2.18 ± 0.79	1.93 ± 0.66

Repeated analysis of variance for Phase 1

Factor	F-value	p-value
Cost function	$F(1.91, 57.34) = 7.84$	$p = 0.001$
Visualizations	$F(2,30) = 0.36$	$p = 0.701$
Cost function x Visualization	$F(3.82, 57.34) = 1.36$	$p = 0.262$

Pair-wise comparisons, Bonferroni tests (regardless of visualization)

NOMINAL[a]	Time	Metabolic	Exploration
Distance	t(32) = -3.18, p = 0.003	t(33) = -0.63, p = 0.53	t(33) = -1.19, p = 0.24
Time		t(32) = -3.89, p < 0.0001	t(32) = -2.89, p = 0.007
Metabolic			t(33) = -1.04, p = 0.31

a. Bonferroni adjusted p-value = 0.008

Simple contrast of Time function

NOMINAL	Distance	Metabolic	Exploration
Time	F(1, 30) = 10.46, p = 0.003	F(1, 30) = 15.13, p = 0.001	F(1, 30) = 8.44, p = 0.007

- Simple main effects within LOEC visualization showed that there was no effect due to cost function (F(3, 28) = 1.85, p = 0.16). However, a single comparison between Exploration and Time cost functions showed significantly less time was spent on Exploration than the Time cost function (pair-wise comparison with least significant difference, p = 0.036).

Repeated analysis of variance for Phase 2

Factor	F-value	p-value
Cost function	F(1, 29) = 17.33	p < 0.0001
Visualizations	F(2, 29) = 0.13	p = 0.88
Scenario	F(1, 29) = 0.34	p = 0.56
Cost function x Visualization	F(2, 29) = 1.65	p = 0.21
Scenario x Visualization	F(2, 29) = 0.39	p = 0.68
Function x Scenario	F(1, 29) = 0.072	p = 0.79
Function x Scenario x Visualization	F(2, 29) = 0.23	p = 0.80

PERCENT TIME SPENT MODIFYING PATH

Descriptive statistics for percent time spent modifying path

Visualization Group	Nominal			Off-Nominal		
	Distance	Time	Metabolic	Exploration	Time	Exploration
Elevation Contours	29.25% ± 22.76	24.09% ± 25.10	32.95% ± 24.84	34.44% ± 27.74	26.56% ± 30.25	32.62% ± 26.39
LOEC	43.28% ± 14.10	44.33% ± 17.61	39.53% ± 24.81	38.94% ± 25.31	41.35% ± 25.31	30.11% ± 26.56
Both visualizations	37.23% ± 23.83	42.39% ± 20.26	35.18% ± 27.29	48.74% ± 28.47	39.11% ± 26.70	40.24% ± 25.80
Total	36.37% ± 20.97	36.56% ± 22.72	35.80% ± 25.01	40.52% ± 27.07	35.41% ± 27.57	34.27% ± 25.81

Repeated analysis of variance for Phase 1

Factor	F-value	p-value
Cost function	F(3, 93) = 0.788	p = 0.504
Visualizations	F(2, 31) = 1.125	p = 0.337
Cost function x Visualization	F(6, 93) = 1.433	p = 0.210

Main effect due to LOEC visualization for Phase 1

Factor	F-value	p-value
Cost function	F(3,96) = 0.86	p = 0.47
LOEC	F(1,32) = 2.32	p = 0.14
Cost function x Visualization	F(3,96) = 1.45	p = 0.23

- Within the Time cost function, LOEC groups (both groups with LOEC visualization) were compared with elevation contours group using a simple effect test of Time (F(1,32) = 6.52, p = 0.016); LOEC participants spent more percent time modifying the Time cost function than the other visualization group.

Simple main effect due to cost function

Visualization	F-value	p-value
Elevations contours	F(3, 29) = 1.30	p = 0.29
LOEC	F(3, 29) = 0.32	p = 0.81
Elevations contours & LOEC	F(3, 29) = 2.15	p = 0.12

Point-wise comparisons within Elevation contours group

NOMINAL	Metabolic	Exploration
Time	t(11) = -2.30, p = 0.042	t(11) = -2.70, p = 0.021

- Point-wise comparison between Exploration and Metabolic cost function within the visualization with both elevation contours & LOEC was significant (t(10) = -2.34, p = 0.041)

Point-wise comparisons for Exploration cost function (Least significant difference test)

NOMINAL	LOEC	Elevation Contours & LOEC
Elevation Contours	p = 0.70	p = 0.22
LOEC		p = 0.41

Repeated analysis of variance for Phase 2

Factor	F-value	p-value
Cost function	$F(1, 31) = 0.25$	$p = 0.62$
Visualizations	$F(2, 31) = 1.04$	$p = 0.37$
Scenario	$F(1, 31) = 2.02$	$p = 0.165$
Cost function x Visualization	$F(2, 31) = 4.10$	$p = 0.026$
Scenario x Visualization	$F(2,31) = 0.61$	$p = 0.55$
Function x Scenario	$F(1,31) = 1.54$	$p = 0.23$
Function x Scenario x Visualization	$F(2,31) = 0.012$	$p = 0.99$

Simple main effect due to cost function for Phase 2

Visualization	F-value	p-value
Elevations contours	$F(1, 31) = 4.01$	$p = 0.054$
LOEC	$F(1, 31) = 3.77$	$p = 0.061$
Elevations contours & LOEC	$F(1, 31) = 0.76$	$p = 0.39$

TRUE TIME

Descriptive statistics for true time

Visualization Group	Nominal				Off-nominal	
	Distance	Time	Metabolic	Exploration	Time	Exploration
Elevation Contours	89.07 ± 35.13	135.12 ± 87.54	94.38 ± 66.78	96.57 ± 72.65	96.37 ± 78.42	56.08 ± 47.93
LOEC	129.24 ± 66.36	155.38 ± 82.18	97.49 ± 52.58	103.62 ± 61.87	141.69 ± 107.77	91.64 ± 81.26
Both visualizations	98.41 ± 61.16	178.61 ± 110.68	99.99 ± 62.49	110.89 ± 41.09	138.48 ± 90.41	103.09 ± 66.41
Total	105.09 ± 56.41	155.75 ± 92.96	97.20 ± 59.28	103.49 ± 58.88	124.66 ± 92.18	82.80 ± 67.28

Repeated analysis of variance for Phase 1

Factor	F-value	p-value
Cost function	$F(3, 93) = 7.70$	$p < 0.0001$
Visualizations	$F(2, 31) = 0.53$	$p = 0.59$
Cost function x Visualization	$F(6, 93) = 0.62$	$p = 0.71$

Simple contrasts

NOMINAL	Distance	Metabolic	Exploration
Time	$F(1, 31) = 10.88$, $p = 0.002$	$F(1, 31) = 15.66$, $p < 0.0001$	$F(1, 31) = 11.61$, $p = 0.002$

Repeated analysis of variance for Phase 2

Factor	F-value	p-value
Cost function	$F(1, 31) = 24.15$	$p < 0.0001$
Visualizations	$F(2, 31) = 1.23$	$p = 0.31$
Scenario	$F(1,31) = 4.62$	$p = 0.040$
Cost function x Visualization	$F(2, 31) = 0.17$	$p = 0.84$
Scenario x Visualization	$F(2, 31) = 0.44$	$p = 0.65$
Function x Scenario	$F(1, 31) = 0.26$	$p = 0.62$
Function x Scenario x Visualization	$F(2, 31) = 0.26$	$p = 0.77$

DIFFERENTIAL COST

Descriptive statistics for differential cost

Visualization Group	Nominal				Off-nominal	
	Distance	Time	Metabolic	Exploration	Time	Exploration
Elevation Contours	9.98 ± 9.17	23.56 ± 18.58	7.48 ± 9.59	4.16 ± 4.11	4.84 ± 15.50	0.13 ± 1.91
LOEC	5.02 ± 2.48	30.63 ± 24.26	10.38 ± 7.17	1.34 ± 1.65	16.68 ± 24.25	3.18 ± 3.30
Both visualizations	7.78 ± 6.36	25.76 ± 15.77	8.72 ± 5.90	3.32 ± 2.17	14.94 ± 30.12	1.44 ± 7.01
Total	7.66 ± 6.82	26.56 ± 19.44	8.82 ± 7.63	2.97 ± 3.05	11.94 ± 23.71	1.54 ± 4.59

Distribution of participants with zero differential cost between visualizations, Phase 1

Cost Function	Pearson χ^2 test	p-value
Distance	$\chi^2\ (2,34) = 1.02$	$p = 0.60$
Time	$\chi^2\ (2,34) = 0.43$	$p = 0.81$
Metabolic	$\chi^2\ (2,34) = 0.47$	$p = 0.79$
Exploration	$\chi^2\ (2,34) = 3.02$	$p = 0.22$

Kruskal-Wallis test results for differential cost across visualizations

Cost Function	Scenario	Kruskal-Wallis, χ^2	p-value
Distance	Nominal	$\chi^2(2,34) = 1.00$	$p = 0.61$
Time	Nominal	$\chi^2(2,34) = 0.53$	$p = 0.77$
Metabolic	Nominal	$\chi^2(2,34) = 0.76$	$p = 0.68$
Exploration	Nominal	$\chi^2(2,34) = 4.99$	$p = 0.082$
Time	Off-nominal	$\chi^2(2,34) = 2.50$	$p = 0.29$
Exploration	Off-nominal	$\chi^2(2,34) = 4.06$	$p = 0.13$

Visualization comparisons between within Exploration cost function (Mann-Whitney tests)

EXPLORATION NOMINAL	LOEC	Elevation Contours & LOEC
Elevation Contours	$Z = -1.54$, $p = 0.12$	$Z = -0.19$, $p = 0.85$
LOEC		$Z = -2.33$, $p = 0.02$

- In Phase 1, there was a significant difference in differential costs between cost functions (Friedman test: $\chi^2(3, N = 34) = 41.37$, $p < 0.0001$).

Wilcoxon Sign test results of pair-wise comparisons for differential cost between cost functions, Phase 1

Cost Function Comparisons	Wilcoxon Sign test & p-value	Result
Distance – Time	$Z = -4.42$, $p < 0.0001$	Distance < Time
Distance – Metabolic	$Z = -0.83$, $p = 0.41$[a]	Distance ≅ Metabolic
Distance – Exploration	$Z = -3.58$, $p < 0.0001$[b,c]	Exploration < Distance
Time – Metabolic	$Z = -4.33$, $p < 0.0001$	Metabolic < Time
Time – Exploration	$Z = -4.83$, $p < 0.0001$	Exploration < Time
Metabolic – Exploration	$Z = -3.61$, $p < 0.0001$	Exploration < Metabolic

a. Only within the LOEC visualization group: $Z = -2.05$, $p = 0.041$
b. Only within elevation contours group: $Z = -1.65$, $p = 0.099$
c. Only within elevation contours & LOEC group: $Z = -1.87$, $p = 0.062$

Distribution of participants with negative differential cost between visualizations, Phase 2

Cost Function	Pearson χ^2 test	p-value
Time	$\chi^2(2,34) = 1.00$	$p = 0.61$
Exploration	$\chi^2(2,34) = 2.55$	$p = 0.28$

Distribution of participants with zero differential cost between visualizations, Phase 2

Cost Function	Pearson χ^2 test	p-value
Time	$\chi^2(2,34) = 1.00$	$p = 0.61$
Exploration	$\chi^2(2,34) = 1.98$	$p = 0.37$

Distribution of participants with negative and zero differential cost between visualizations, Phase 2

Cost Function	Pearson χ^2 test	p-value
Time	$\chi^2(4,34) = 2.55$	$p = 0.64$
Exploration	$\chi^2(4,34) = 5.23$	$p = 0.27$

Wilcoxon Sign test results for differential costs between cost functions

Cost Function Comparisons	Wilcoxon Sign test & p-value			
	Regardless of visualization	Elevation contours	LOEC	Both visualizations
Time off-nominal – Exploration off-nominal	Z = -2.34, p = 0.019	Z = -0.80, p = 0.42	Z = -1.48, p = 0.14	Z = -1.60, p = 0.11
Time nominal – Time off-nominal	Z = -2.67, p = 0.008	Z = -1.87, p = 0.062	Z = -1.42, p = 0.16	Z = -1.25, p = 0.21
Exploration nominal – Exploration off-nominal	Z = -1.18, p = 0.24	Z = -2.58, p = 0.01	Z = -1.78, p = 0.074	Z = -0.62, p = 0.53

NON-OPTIMAL SATISFICING

Descriptive statistics for non-optimal satisficing (cost surplus)

Visualization Group	Nominal				Off-nominal	
	Distance	Time	Metabolic	Exploration	Time	Exploration
Elevation Contours	0.00 ± 0.00	0.05 ± 0.15	0.08 ± 0.17	0.20 ± 0.39	6.18 ± 9.02	1.01 ± 1.26
LOEC	0.05 ± 0.12	0.84 ± 2.04	0.17 ± 0.24	0.07 ± 0.13	3.86 ± 6.04	1.05 ± 1.44
Both visualizations	0.00 ± 0.00	1.09 ± 2.88	0.04 ± 0.14	0.19 ± 0.40	4.18 ± 8.03	1.42 ± 2.18
Total	0.02 ± 0.07	0.66 ± 2.02	0.10 ± 0.19	0.16 ± 0.33	4.80 ± 7.66	1.15 ± 1.60

Descriptive statistics for non-optimal satisficing (time surplus)

Visualization Group	Nominal				Off-Nominal	
	Distance	Time	Metabolic	Exploration	Time	Exploration
Elevation Contours	27.14% ± 10.87	21.68% ± 19.89	32.53% ± 28.83	42.92% ± 27.16	36.73% ± 22.10	54.69% ± 28.39
LOEC	23.21% ± 21.01	18.62% ± 22.78	39.09% ± 23.19	32.80% ± 20.52	30.38% ± 31.45	38.42% ± 28.44
Both visualizations	33.87% ± 25.99	20.37% ± 22.48	31.65% ± 28.33	29.36% ± 23.49	29.05% ± 28.56	34.78% ± 30.92
Total	28.04% ± 19.93	20.27% ± 21.07	34.37% ± 26.35	35.26% ± 23.99	32.19% ± 26.86	42.99% ± 29.71

Repeated analysis of variance for Phase 1, time surplus

Factor	F-value	p-value
Cost function	F(2.21, 68.56) = 3.11	p = 0.046
Visualizations	F(2, 31) = 0.15	p = 0.86
Cost function x Visualization	F(4.42, 68.56) = 0.65	p = 0.65

Simple contrast of time surplus, Phase 1

NOMINAL	Distance	Metabolic	Exploration
Time	F(1,31) = 2.27, p = 0.14	F(1,31) = 12.76, p = 0.001	F(1,31) = 6.24, p = 0.018

Point-wise comparisons for Exploration function (time surplus), least significant difference test

NOMINAL	LOEC	Elevation Contours & LOEC
Elevation Contours	p = 0.32	p = 0.19
LOEC		p = 0.74

Kruskal-Wallis test for non-optimal satisficing (cost surplus), Phase 2

Cost Function	Scenario	Kruskal-Wallis test	p-value
Time	Off-nominal	$\chi^2(2, 33) = 0.77$	p = 0.68
Exploration	Off-nominal	$\chi^2(2, 33) = 0.25$	p = 0.88

Wilcoxon Sign test results of pair-wise comparisons for cost surplus between cost functions, Phase 2

Cost Function Comparisons	Wilcoxon Sign test
Time off-nominal – Exploration off-nominal	Z = -3.36, p = 0.001
Time nominal – Time off-nominal	Z = -2.14, p = 0.032
Exploration nominal – Exploration off-nominal	Z = -2.54, p = 0.011

Repeated analysis of variance (time surplus) for Phase 2

Factor	F-value	p-value
Cost function	F(1, 31) = 8.24	p = 0.007
Visualizations	F(2,31) = 2.07	p = 0.14
Scenario	F(1,31) = 4.96	p = 0.033
Cost function x Visualization	F(2,31) = 0.69	p = 0.51
Scenario x Visualization	F(2,31) = 0.20	p = 0.82
Function x Scenario	F(1,31) = 0.25	p = 0.62
Function x Scenario x Visualization	F(2,31) = 0.012	p = 0.99

- Correlations time surplus versus true time (off-nominal condition):
    - Time function, Pearson correlation test = -0.66, p < 0.0001.
    - Exploration function, Pearson correlation test = -0.73, p < 0.0001

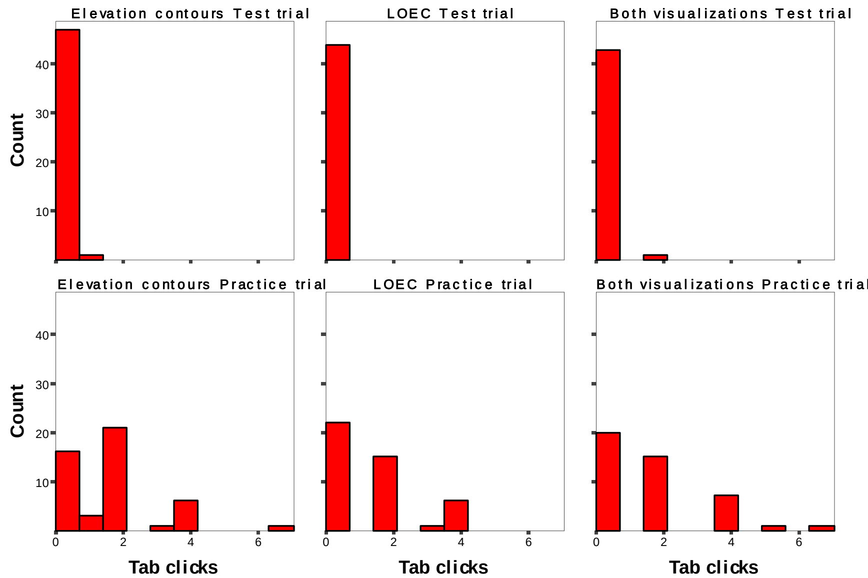
OTHER ANALYSES

Kolmogorov-Smirnov normality tests

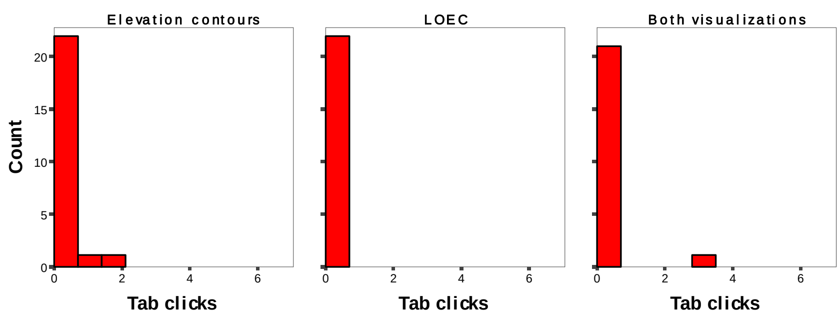
Dependent variable	K-S test, Z	p-value
Path cost errors	Z = 4.34	p < 0.0001
Time penalty	Z = 1.99	p = 0.001
Total time	Z = 1.19	p = 0.12
True time	Z = 1.41	p = 0.037

Spearman's rho correlations between path cost errors and time dependent variable

Time dependent variable	Correlation coefficient	p-value
Time penalty	0.082	p = 0.25
Total time	0.090	p = 0.20
True time	0.065	p = 0.36



Histograms of total instances cost function tab was clicked. Columns, visualization types; top row, nominal test trials; bottom row, practice trials



Histograms of total instances cost function tab was clicked, off-nominal test trials only. Columns, visualization types.

COGNITIVE STRATEGIES

Descriptive statistics of path cost errors and Mann-Whitney test comparisons across strategy types for path cost errors

Cost Function	Manual sensitivity analysis	"Whole-path" sensitivity analysis	Mann-Whitney test & p-value
Distance	1.03 ± 0.03	1.02 ± 0.03	$Z = -0.69, p = 0.49$
Time	1.60 ± 0.14	1.61 ± 0.15	$Z = -0.37, p = 0.72$
Metabolic	1.07 ± 0.02	1.08 ± 0.04	$Z = -0.75, p = 0.45$
Exploration	1.06 ± 0.02	1.06 ± 0.02	$Z = -0.28, p = 0.78$
Time (off-nominal)	1.51 ± 0.20	1.59 ± 0.20	$Z = -1.14, p = 0.26$
Exploration (off-nominal)	1.10 ± 0.03	1.12 ± 0.05	$Z = -0.73, p = 0.47$

Descriptive statistics of distance errors

Cost Function	Path error based on distance
Distance	1.03 ± 0.04
Time	1.12 ± 0.07
Metabolic	1.13 ± 0.04
Exploration	1.06 ± 0.04
Time (off-nominal)	1.08 ± 0.04
Exploration (off-nominal)	1.07 ± 0.05

Repeated analysis of variance for nominal conditions, distance errors

Factor	F-value	p-value
Cost function	$F(1,99) = 34.48$	$p < 0.0001$

- Visualization was not used as a test condition to analyze shortest path heuristic because previous experimental results indicate that there is no main effect due to visualization. Furthermore, including it as a condition did not reveal significant differences among visualization groups.

Simple contrast of distance errors, nominal conditions

NOMINAL	Time	Metabolic	Exploration
Distance	$F(1,33) = 48.3, p < 0.0001$	$F(1,33) = 116.0, p < 0.0001$	$F(1,33) = 7.20, p = 0.011$
Time		$F(1,33) = 0.72, p = 0.40$	$F(1,33) = 19.5, p < 0.0001$
Metabolic			$F(1,33) = 53.0, p < 0.0001$

Repeated analysis of variance for off-nominal conditions, distance errors

Factor	F-value	p-value
Cost function	$F(1,33) = 19.46$	$p < 0.0001$
Scenario	$F(1,33) = 3.05$	$p = 0.09$
Cost function x Scenario	$F(1,33) = 9.61$	$p = 0.004$

Point-wise comparisons across scenarios within cost function (distance errors), least significant difference test

	Nominal vs. Off-Nominal p-value
Time	$p = 0.003$
Exploration	$p = 0.36$

APPENDIX C: META-ANALYSIS ASSESSING SENSITIVITY ANALYSIS

A meta-analysis was conducted in order to assess the effect of sensitivity analysis across both experiments. This analysis would include all participants, 61 in total, and include all test trials (a total of 8). Thus, participants were ranked in the following manner:

- Every participant was assigned a sensitivity analysis type: 0 if they chose whole-path sensitivity analysis, and 1 if they chose path modifications.

- For every participant and for each function, a performance score was assigned. Performance scores ranged from 1 to 3. A score of 1 indicated that the participant had one of the smallest path cost errors for that trial. Similarly, 3 indicated poor performance. Score was assigned based on the average and standard deviations for that trial. A score of 2 was awarded to participants whose path cost errors were ± 1 standard deviation from the mean error of that trial. Above and below one SD, these participants were given scores of 1 and 3, respectively.

- For every participant and for each function, a ranking of modification time was given. Since the percent modifying time ranged from 0 to 85%, 9 bins were created, one for every 10 percent increment.

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