Risk Attitude Informed Route Planning in a Simulated Planetary Rover

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RISK ATTITUDE INFORMED ROUTE PLANNING IN A SIMULATED PLANETARY ROVER

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ABSTRACT

Algorithms used in rovers for route planning often focus on finding the shortest path between two points, but rarely take into account the risk to the physical roving system of taking a path. One issue presented by route planning optimized for risk is varying risk attitudes, which can lead to vastly different routes being chosen. A risk attitude is a preference concerning acceptable levels of risk to perform a specific action. The field of Prognostics and Health Management (PHM) aims to predict and prevent mechanical failure in electrical and mechanical systems, and can be used to inform route planning by assessing risk associated with taking an action. A method has been developed and is presented in this paper for Risk Attitude Informed Route-planning (RAIR) that takes into account the calculated risk, the benefit, and risk attitude and selects the optimal route. The risks to the rover will be calculated by using rover PHM data, terrain information, and Function Failure Identification Propagation (FFIP) to determine risk of specific routes. The route is navigated incrementally by selecting the best route across a small segment and then determining the best route from the new position until the rover has reached the final destination. Results of experiments utilizing a simulated planetary rover navigating between points using RAIR are presented in this paper and the effectiveness of the method is discussed. Improved route planning through RAIR enables more autonomous navigation of hazardous and remote environments that accurately reflects the desired risk attitude without direct human planning or interaction than is currently available, thus reducing cost and time for exploratory rover missions to accomplish mission objectives.

INTRODUCTION

Planetary rovers are an incredible tool for exploration, [1] but are highly dependent on human operators in order to continue functioning. Route planning algorithms [2] can improve rover autonomy by reducing the amount of human time that must be spent planning routes for the rover. Route planning algorithms can be enhanced by the use of Prognostics and Health Management (PHM) [3-5] techniques which can predict and prevent mechanical and electrical failures in a system. This can extend the mission life of a rover, increasing the effectiveness of the rover as a scientific tool. Traditional route planning algorithms do not consider differing risk attitudes in the route planning decision making process. Risk attitudes are varying preferences towards acceptable levels of risk when performing actions, and can vary between individuals based on a number of factors. By utilizing risk attitudes in route planning, paths can be optimized to reflect the risk preferences of the operators and can therefore behave more autonomously in a way that is acceptable to the operators. This paper presents a novel method for Risk Attitude Informed Route-planning (RAIR) that uses optimization equations to enable decision making based on risk calculated using Function Failure Identification and Propagation (FFIP) [6-8].

Specific Contributions

The focus of this paper is on a novel method for mobile system operation optimization using PHM data and risk attitude information through the application of RAIR. RAIR allows for varying risk attitudes to be represented through behavior giving a higher degree of control over the behavior of a mobile system in a previously unknown situation. By determining the optimum risk attitude for the mobile system, a higher likelihood of mission success, as defined by reaching a target location without operator intervention and without failure, can be achieved.

BACKGROUND

RAIR relies upon several topics including PHM techniques, optimization theory, functional failure modeling, and risk attitudes. Traditional PHM-informed route planning does not consider varying risk attitudes which lead to methods that are rigid and inherently biased towards an arbitrary risk attitude. RAIR aims create varying risk attitudes by modifying parameters in a constrained non-linear objective function.

Autonomous Mobility in Robotics

Autonomous mobility in robotic systems has a long history. Some of the earliest examples of autonomous mobile robots were William Grey Walter's robotic tortoises, which navigated towards lights in the early 1950s and had control circuits containing vacuum tubes for decision making [9, 10]. Over the past several decades, autonomous mobile robots have become significantly more advanced and now utilize advanced controls to command their complex systems [11]. The National Aeronautics and Space Administration (NASA) currently have two active rovers on the Martian surface: Opportunity and Curiosity [12, 13]. NASA has also put two other rovers, Spirit and Sojourner, on Mars since 1997 [14]. Spirit is the twin of Opportunity sharing the same design and having been on Mars approximately the same amount of time. Spirit however failed prematurely due to becoming trapped in a dust pit on the ground and losing mobility. The dangers of unknown terrain conditions and large signal delay before human mitigating action can be initiated are a great threat in robotic planetary exploration. Curiosity is facing a similar fate as a result of unexpected damage to her wheels from unforeseen terrain conditions. The enhancement of robotics for planetary exploration through artificial intelligence and increased autonomy has a great potential and could greatly increase the breadth of human knowledge [15].

Route Planning

Route planning was first developed in the late 1960's [16] and has been used widely in a variety of fields including transportation infrastructure, aerospace, automotive, and robotics [17-20]. In the field of robotics, route planning can be used in commercial applications in warehouse settings, security, tour guiding, or exploration. NASA researchers developed the OASIS autonomous science system [15] which provides a method for planning of rover scientific activities. OASIS allows for the managing of long term objectives with opportunistic scientific actions while generating a mission and route plan. Many route planning techniques involve the use of optimization techniques [21] to determine the best available path. These specific optimization objective functions [22] can vary, but generally are a non-linear constrained function that looks at the direct linear distance between two discrete points. PHM-enabled route planning has been under development for the past several years [22-24] and has shown to be effective, but has not taken into account varying risk attitudes in their decisions.

Prognostics and Health Management

PHM attempts to predict and mitigate electrical and mechanical failure in systems. Many methods exist for PHM analysis and every method possesses strengths and weaknesses for particular applications. The process of making decisions based on PHM information is referred to as Prognostic-Enabled Decision Making (PDM) [23] and can be used to decide what option presents the allowable level of risk to the system. This can be an incredibly useful tool in PHM analysis of a system because it can be used to calculate the potential damage that could be caused to a system by one component failing. One of the building blocks of PHM is the development of mathematic models of physical systems such as power, mobility, or control systems. These models are necessary for PHM because they offer a prediction of the results of taking an action on the physical stature of the system. Another critical aspect of PHM in a system is physical instrumentation in order to monitor the condition of the system. This is important because system models may not account for an unforeseen interaction affecting the system and live monitoring of the system is the only viable option for knowing its current status.

Functional Modelling

Functional modelling is used to represent complex systems from a functional basis. One common tool used for functional modelling is the Functional Flow Diagram (FFD) [25]. The FFD represents functions within a system as blocks and tracks the flow of energy, material, and information through the system. The structure of a FFD is similar to that of a flow chart where the system blocks are arranged spatially and then the flows passing between are represented by arrows. The convention used for the flows in this paper are thick arrows representing object flow, thin arrows representing energy flow, and dashed arrows representing information flow. A color coding system is generally used to represent various specific subsets of flows. FFDs generally start with a very high-level black box model of the system inputs and outputs. This black box model tracks flows entering and exiting the system but doesn't take into account any of the flows internal to the whole system. Below this layer is the system level. At this level, basic systems are described and related to each other, such as power, mobility, or control systems. The next layer down is the sub-systems. Sub-systems are the functions that make up the systems. The sub-system level is focused on in this paper. The FFD can be broken down even further in sub-sub-systems and so on until the desired level of representation is achieved.

Function Failure Identification and Propagation (FFIP) can be used in tandem with FFD to analyze the flow of failure through a system. Failure in this case is defined by the loss of functionality. If the loss of functionality leads to system-wide failure, then it is deemed critical failure. FFIP looks at risk of failure at a point in a complex system and then analyzes the probabilities of the failure propagating through the system and causing critical failure. FFIP can be further enhanced through the application of Failure Flow Decision Functions (FFDF) [26] which can be used to make decisions that are intended to mitigate critical system failure.

Risk Attitude

Risk attitude is a term that describes a preference towards acceptable levels of risk [27, 28]. Risk can be defined as a parameter that describes the probability of damage to a system. Risk attitudes can be highly variable depending on the individual and can be influenced by culture, environment, work conditions, past experiences, and company culture, among other influences. Generally risk attitudes can be depicted by a utility function taking the form of a quadratic, exponential, or logarithmic curve [29]. Broad classifications of risk attitudes can be broken down into the two categories of risk aversion and risk tolerance [5]. The risk averting attitude can be described as taking the expected value and taking actions to preserve the value. An example of this attitude would be taking a dollar and putting it in a savings account with modest interest. This would have an incredibly low risk of loss of the money and a high chance of gaining a small amount. This is the more conservative of the two broad categories. Risk tolerant individuals are characterized by taking a higher risk of loss for a lower probability of a higher reward. An example of this behavior would be taking a dollar and using it to buy a lottery ticket with the potential of winning some large amount of money. This would have an incredibly low probability of making a large amount of money and a high probability of losing all the money. This is complicated further because risk attitude is not a strict binary and can include a wide variety of differing magnitude and attitudes towards differing classes of risk [27].

METHODOLOGY

RAIR relies upon PHM, functional failure modeling, optimization techniques, and risk attitudes in order to determine the best available route to a target destination. The core of RAIR is an objective function that takes into account the most direct path to the target location, the current status of the roving system, the environment surrounding the roving system, the failure probability of sub-systems, and the probability of critical failure through propagation of failure through the system.

The failure of the system is analyzed through FFIP analysis which utilizes the Function Flow Diagram (FFD) shown in Figure 1.

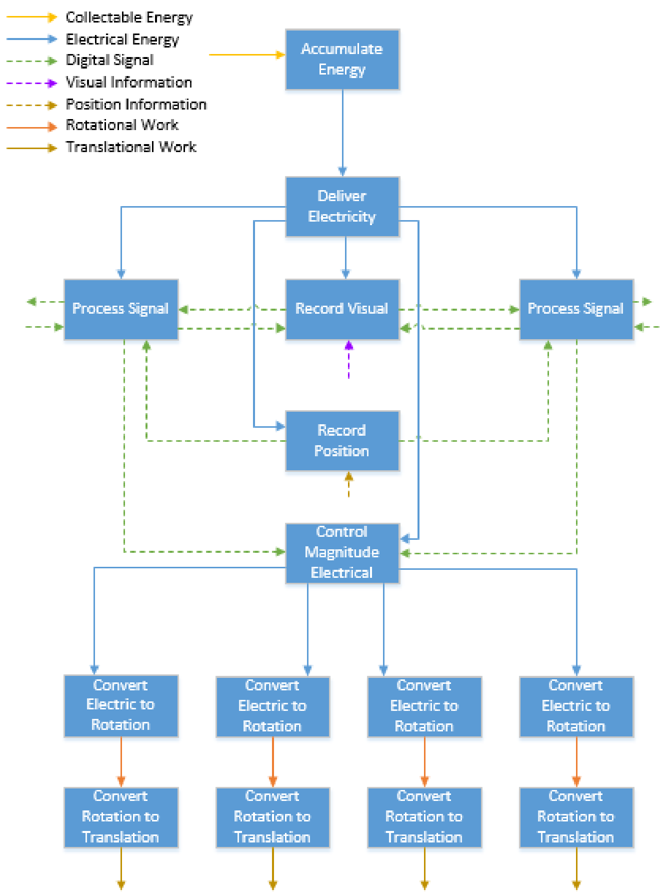

FIGURE 1. FUNCTION FLOW DIAGRAM OF SIMPLE ROVER

The RAIR algorithm consists of 3 phases. The first is situational analysis. This consists of surveying the terrain around the rover to determine what paths are available. This can be performed at variable radiuses out from the rover and variable numbers of finite points. A large radius with a smaller number of points along the circumference of the area is preferable for a low risk environment when the terrain is relatively homogenous and hazard-free. A small radius with a larger number of points along the circumference is preferable for a high risk environment when the terrain is non-homogenous and contains hazards. The second phase is the decision phase which looks at the points selected in phase 1 and determines the optimal point to navigate towards. This is performed using a weighted objective function that looks at the potential distance towards object gained; the magnitude of potential risk caused by the action, and then weights them appropriately using the risk tolerance (ρ). The third phase is the navigation phase, where the rover orients itself in the desired direction and then proceeds to the chosen point. The process then repeats from phase 1. A detailed breakdown of the method can be found below. Equation 1 details the objective function used.

1. The rover determines its current location and heading.
2. The rover determines the direction and distance to target position.
3. The rover checks status of mechanical and electrical sub-systems.
4. The rover looks at desired number of points evenly distributed at desired radius away from the rover.
5. The rover determines direction to point, incline of surface towards point, distance between point and final destination, and environmental factors at the point.
6. The rover takes information for each point and uses it to populate the variables of the objective function.
7. The rover records the values of the objective function for each point.
8. The highest scoring point is selected as the next point to navigate to.
9. The rover rotates to align its heading with the desired point.
10. The rover drives to the desired point.
11. The process is repeated from step 1.

$$\Omega = \frac{\theta - \theta_p}{(\theta + \theta_p)/2} + \rho \frac{\Delta L - \Delta L_p - 1}{(\Delta L - \Delta L_p + 3)/2} + \int \eta \, dl$$

EQUATION 1. OBJECTIVE FUNCTION

Where θ and θ_p represent the ideal and inspected point incline, ΔL and ΔL_p represent the length to the target, ρ presents the risk tolerance, η represents the projected hazard rate at a point, and l represents the linear path between the current location and the target destination.

In addition to these steps for navigating to the desired position, additional steps can be taken to determine the success of the rover in its navigation. If the rover becomes stuck and is unable to make significant progress across hazardous terrain or determines that taking any action would present too great of a risk to move closer to the target, the rover will enter an idle state after a specific period of time. Alternatively, after the rover has reached its target destination it will enter the idle state.

By following the above listed steps, a roving system can quickly and safely navigate through a largely unknown environment to a desired location. This method can be adapted for aquatic, aerial, or other terrestrial applications, by modifying the objective function to consider new environmental factors or system components. The versatility of RAIR also allows for it to be implemented on a wide variety of systems from low to high complexity and cost. This makes RAIR a valuable tool for optimization of system design for risk attitudes by allowing for more robust systems to take greater risks and less robust systems to take fewer risks.

CASE STUDY

To analyze the effectiveness of RAIR, a case study was performed on a simulation of a Mars planetary rover similar to the NASA Mars rovers Opportunity and Spirit. Simulations were performed utilizing a rover with a RAIR-enabled variable risk tolerance. The RAIR-enabled rovers had a risk tolerance weight of 5, 10, 20, and 50. The risk tolerance weight (ρ) is a value that multiplies the perceived reward for an action, and therefore encourages the rover to drive towards the target. Preliminary testing showed that a ρ of 1 would almost always lead to a virtually immobile rover that had determined that the risk or locomotion was not worth reaching the target.

A simulation was developed in Java of representative Martian landscape that randomly generates topography for the rover to navigate. Figure 2 displays the user interface of the simulation. Figure 3 displays a close up view of the rover on the terrain. Figure 4 displays a zoomed out view of the first map used in the testing. Low points on the map are colored dark red and high points are green.

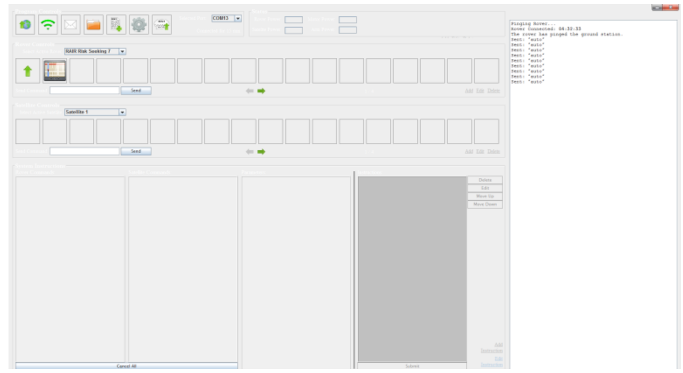

FIGURE 2. SIMULATION USER INTERFACE

FIGURE 3. CLOSE UP VIEW OF A GENERATED MAP

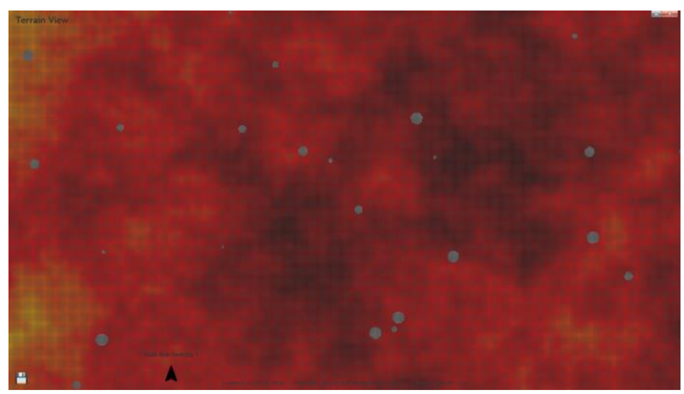

FIGURE 4. ZOOMED OUT VIEW OF A GENERATED MAP

The simulated Martian topography is rather turbulent like a series of sand dunes and hills, and has a high potential for the rover to slip. This would be representative of a terrain that would be very difficult to navigate through using traditional rover navigation. This terrain was chosen in order to lead to a larger degree of difficulty and insure that all rovers could not easily reach the target destination.

The temperature of the Martian surface is taken to be -30°C which is a moderate Martian temperature. This affects the cooling rates of our electronics, which was used as a metric to determine probability of system failure.

Four different maps were generated for this case study. This was to ensure that the map had not biased the results by being particularly favorable for a single method. The rovers were tasked with travelling approximately 100 m which was selected to represent a distance large enough to get a significant sample, but still small enough to be computationally feasible to perform multiple trials. Each method was tested eight times on each map giving a total of 32 trials for each rover and a total of 128 tests to provide enough data to allow for meaningful analysis. As the rover travels along the path, it records its current status and probability of critical failure.

Using RAIR and analyzing risk to the system over time through active FFIP, the risk of the mission could be gathered. Results and discussion of the RAIR case study can be found in the next section.

RESULTS AND DISCUSSION

RAIR was shown to provide a significant difference in rover performance. Lower risk tolerances lead to generally safer results, as seen in Figure 13. The averaged mission risk in the form of hazard rate to the rovers was found to be 2.51%, 2.57%, 2.54%, and 2.64% for the risk tolerance of 5, 10, 20, and 50 respectively. The average mission life before 95% of the rovers were expected to fail was found to be 8.2, 7.3, 7.8, and 6.4 years for the risk tolerances of 5, 10, 20, and 50 respectively. The mission hazard rate for each map can be seen in Table 1. Figures 5 through 8 show the routes taken between the start position and target point. The start point is near (0, 0) and the target point is near (70, 70).

TABLE 1. HAZARD RATE BY MAP

Mission Hazard Rate (%)					
	Map				
ρ	1	2	3	4	ρ Mean
5	2.49%	2.63%	2.42%	2.51%	2.51%
10	2.72%	2.72%	2.44%	2.41%	2.57%
20	2.57%	2.60%	2.46%	2.51%	2.54%
50	2.80%	2.85%	2.42%	2.49%	2.64%
Map Mean	2.65%	2.70%	2.44%	2.48%	

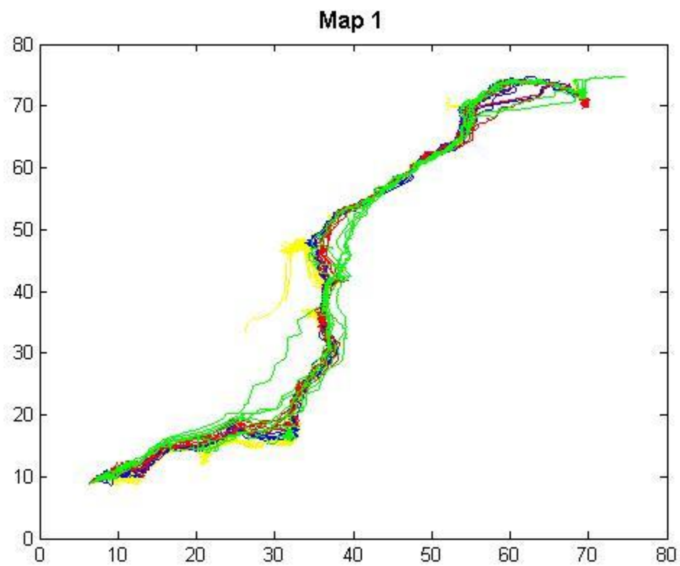

FIGURE 5. PLOT ROVER PATHS ON MAP 1. YELLOW: ρ=5, BLUE: ρ=10, RED: ρ=20, GREEN: ρ=50

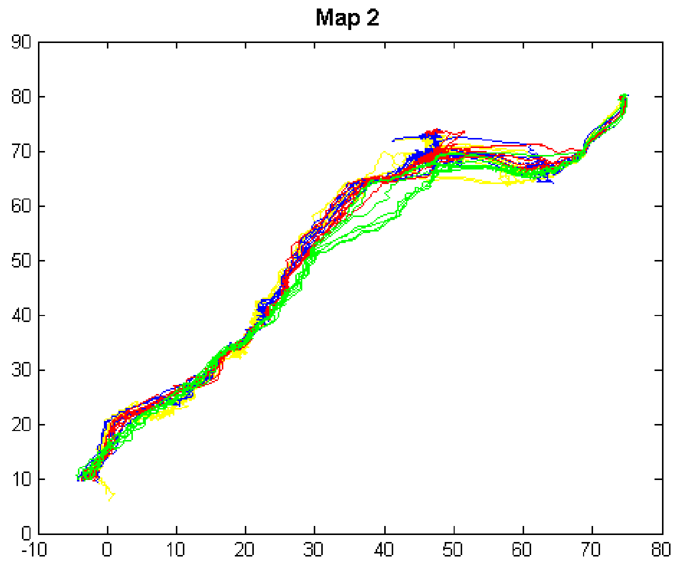

FIGURE 6. PLOT ROVER PATHS ON MAP 2. YELLOW: ρ=5, BLUE: ρ=10, RED: ρ=20, GREEN: ρ=50

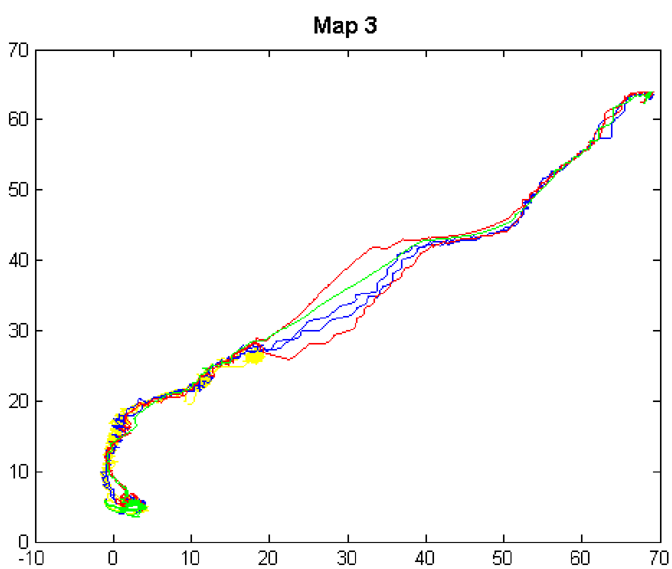

FIGURE 7. PLOT ROVER PATHS ON MAP 3. YELLOW: ρ=5, BLUE: ρ=10, RED: ρ=20, GREEN: ρ=50

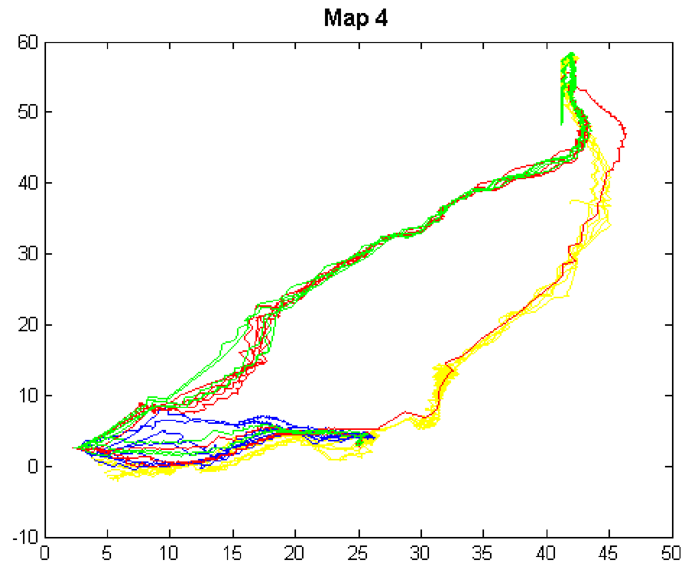

FIGURE 8. PLOT ROVER PATHS ON MAP 4. YELLOW: ρ=5, BLUE: ρ=10, RED: ρ=20, GREEN: ρ=50

Most of the rovers tried to take a similar path for a particular map. Map 3 is particularly interesting, because it shows many of the rovers taking a very similar path, but only a small number of the more risk tolerant rovers made it through to the end.

The calculated hazard rates vs time are displayed in Figures 9-13. A hazard rate is probability of system failure at an instantaneous time. The hazard rates were calculated by using a normal distribution of failure over the operating status of the components of the rover. Figure 14 shows the calculated failure distribution, which is the percentage of expected failures over time. The failure distributions were found by using the mean of the hazard rates for each risk tolerance in an exponential failure distribution.

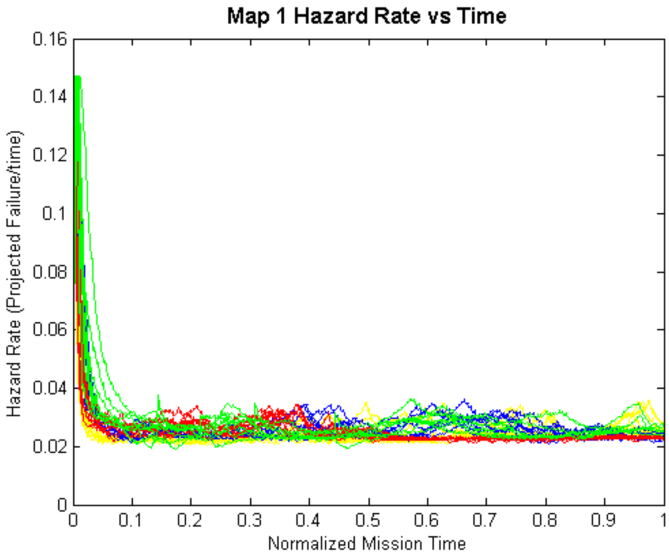

FIGURE 9. ROVER HAZARD RATE VS TIME ON MAP 1. YELLOW: ρ=5, BLUE: ρ=10, RED: ρ=20, GREEN: ρ=50

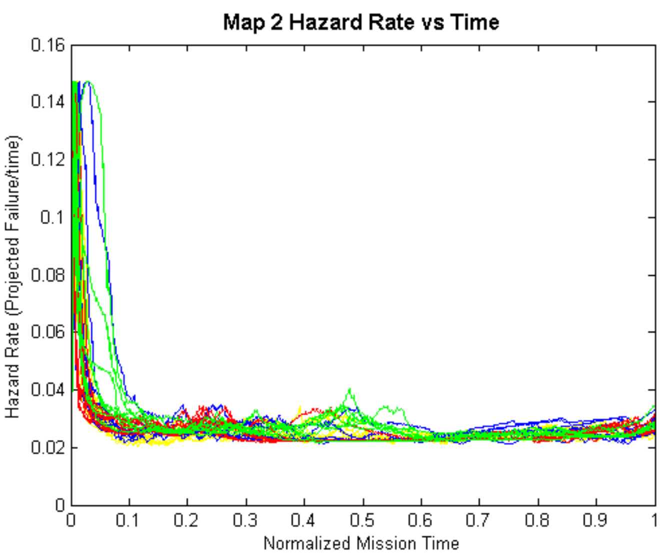

FIGURE 10. ROVER HAZARD RATE VS TIME ON MAP 2. YELLOW: ρ=5, BLUE: ρ=10, RED: ρ=20, GREEN: ρ=50

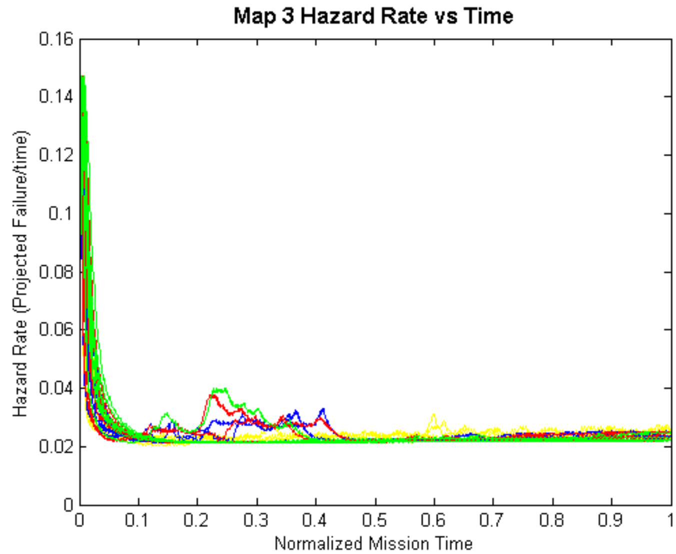

FIGURE 11. ROVER HAZARD RATE VS TIME ON MAP 3. YELLOW: ρ=5, BLUE: ρ=10, RED: ρ=20, GREEN: ρ=50

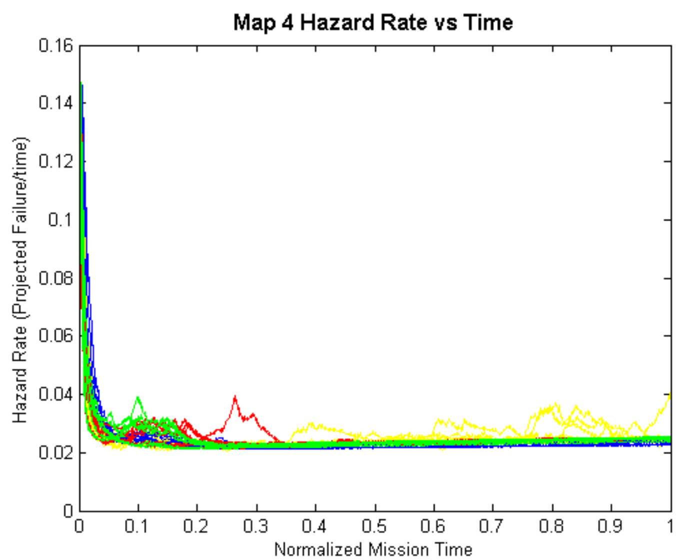

FIGURE 12. ROVER HAZARD RATE VS TIME ON MAP 4. YELLOW: ρ=5, BLUE: ρ=10, RED: ρ=20, GREEN: ρ=50

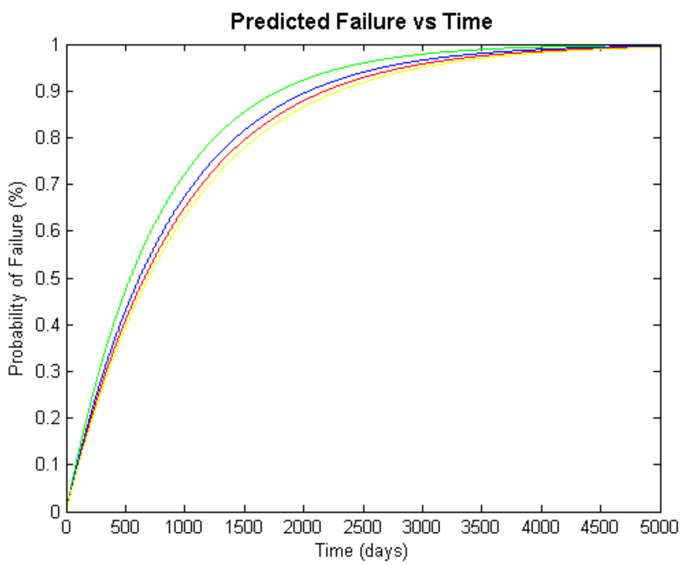

FIGURE 13. FAILURE DISTRIBUTIONS. YELLOW: ρ=5, BLUE: ρ=10, RED: ρ=20, GREEN: ρ=50

One trend through the data is that the risk tolerances of 10, 20, and 50 tended to be more successful at reaching the target location than the rovers with a risk tolerance of 5. The risk tolerance of 5 reached the target destination in 19% of the trials. The rovers with the tolerance of 10, 20, and 50 all reached the destination approximately 50% of the time. The cause for this trend appears to be that the rover with more risk aversion tends to not want to risk climbing steep hills and ends up staying in a valley driving back and forth until it shuts down. This implies that there is a minimum level of risk necessary to navigate the terrain. Table 2 shows the percentage of rovers to reach the Target position by map.

TABLE 2. PERCENT ROVERS TO REACH TARGET BY MAP

Mission Success					
	Map				
ρ	1	2	3	4	ρ Mean
5	13%	63%	0%	0%	19%
10	100%	88%	13%	0%	50%
20	100%	75%	13%	0%	47%
50	100%	100%	13%	0%	53%
Map Mean	78%	81%	9%	0%	

In general, the higher risk tolerances were more capable of reaching the target destination with comparatively little significant differences between the results of risk tolerances of 10, 20, and 50. The failure rates for the higher risk tolerances tended to be lower with the risk tolerance of 5 having a 95% predicted failure after 8.2 years and the risk tolerance of 50 having a 95% predicted failure rate after 6.4 years. One final notable trend was that the risk attitude of 10 had a higher success rate of reaching the target destination than the risk attitude of 20, and a higher hazard rate. This is discussed further in the Conclusion and Future Work section.

CONCLUSION AND FUTURE WORK

The RAIR method presented in this paper is a novel method for planning routes that is optimized for risk attitudes using PHM methods for decision making. Previously, route planning algorithms had not taken into account variable risk attitudes in determining the optimal path. By using risk attitudes to inform the route planning, paths that are more representative of the operators desired level of risk can be achieved.

RAIR was shown to have a significant impact on the level of risk presented to a system. This is largely in part to a reduced amount of time spent trying to climb overly steep hills leading to slipping and overheating.

One interesting result was that the risk tolerance of 10 seemed to accrue more risk than the risk tolerance of 20, but also managed to reach the target destination more often. This implies that there may be a more complex relationship between the risk tolerance applied to the optimization formula, and the actual risk that accrues. One possible explanation is that there is a region of risk tolerance where a rover is more likely to take a moderate risk, moderate reward action, and that these end up providing less reward over the long run than taking slightly more risk for more reward. Future studies should be performed to better study this relationship.

Further refinement of RAIR will lead to a greater degree of control over acceptable level of risk and implementation of learning techniques could lead to a self-adjusting RAIR that could self-optimize towards the desired risk level. Analysis of RAIR in use for more complex task completion could also provide optimized methods for determining task order in swarms or of solitary rovers. Finally combination of RAIR with a PHM Informed Damage Aversion Algorithm (PIDAA) [30] could allow the rover to better react to instantaneous risk instead of avoiding future risk while still potentially putting itself in harm's way.

Future work will focus on the development of rovers idealized for maximum mission life using RAIR by varying the robustness of the design of the rover. Rather than building a rover meant for the harshest conditions and then using it in a very risk averse manner, or building a rover meant for minimal risk environments but then operating the rover in a very risk tolerant fashion, a rover can be designed for the risk attitudes of the operators. This could lead to greatly improved behavior for economical design.

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