SELF-RELIANT ROVER DESIGN FOR INCREASING MISSION PRODUCTIVITY

Daniel Gaines[1], Joseph Russino[1], Gary Doran[1], Ryan Mackey[1], Michael Paton[1], Brandon Rothrock[1], Steve Schaffer[1], Ali-akbar Agha-mohammadi[1], Chet Joswig[1], Heather Justice[1], Ksenia Kolcio[2], Jacek Sawoniewicz[1], Vincent Wong[1], Kathryn Yu[1], Gregg Rabideau[1], Robert Anderson[1], Ashwin Vasavada[1]

[1]*Jet Propulstion Laboratory, Pasadena, California, US, E-mail: firstname.lastname@jpl.nasa.gov*
[2]*Okean Solutions, Seattle, Washington, E-mail: ksenia@okeansolutions.com*

Abstract

Achieving consistently high levels of productivity has been a challenge for Mars surface missions. While the rovers have made major discoveries and dramatically increased our understanding of Mars, they often require a great deal of effort from the operations teams, and achieving mission objectives can take longer than anticipated. The objective of this work is to identify changes to flight software and ground operations that enable high levels of productivity with reduced reliance on ground interactions. This will enable the development of Self-Reliant Rovers: rovers that make use of high-level guidance from operators to select their own situational activities and respond to unexpected conditions, all without dependence on ground intervention. In this paper we describe the system we are developing and illustrate how it enables increased mission productivity.

1 INTRODUCTION

Maintaining high productivity for the Mars exploration rover missions is very challenging. While the operations teams have achieved impressive accomplishments with the rovers, doing so often requires significant human effort in planning, coordinating, sequencing, and validating command products for the robots. A primary reason for these productivity challenges is the heavy reliance on interaction between the rovers and ground operators in order to accomplish mission objectives. For example, prior rovers depend on operators to provide a detailed schedule of activities, select science targets, navigate around slip hazards, and recover from anomalies. When combined with the limited communication opportunities between the rovers and human operators, this reliance on ground interaction results in under-utilization of vehicle resources and increased days on Mars to accomplish mission objectives.

The objective of our work is to identify changes to flight software and mission operations that improve rover efficiency and reduce dependency on ground interactions. This will facilitate the development of Self-Reliant Rovers: rovers that make use of high-level guidance from operators to select their own situational activities and respond to unexpected conditions, all with reduced reliance on human intervention.

Although our objective is to reduce the reliance on ground support in order to promote productivity, we are by no means attempting to remove human operator involvement. To the contrary, our objective is to increase the scope of operator input so that operators can effectively guide rover activity without requiring up to date knowledge of the rover and its environment.

This paper will present the Self-Reliant Rover design and illustrate how it enables rovers to maintain high levels of productivity. In this paper, we will highlight four main components of the design:

Campaign Intent: Allows operators to provide the rover with high-level guidance over the rover's activity planning and autonomous science

Slip-aware navigation: Enables the rover to assess the amount of predicted slip in its environment and plan safe paths to avoid both geometric and slip hazards.

Model-based health assessment: Improves the rover's ability to detect and isolate problems, and increases the range of problems from which it can recover on its own

Global localization: Enables the rover to remove positional knowledge error that accumulates during navigation

2 OVERVIEW OF THE SELF-RELIANT ROVER DESIGN

We are designing the Self-Reliant Rover system within the context of the Jet Propulsion Laboratory flight software architecture [1]. Figure 1 provides an overview of this architecture and the changes we are introducing.

The JPL architecture consists of components organized into three layers: behaviors, activities, and functions. Each successive layer has a reduced degree of autonomy, fewer interactions with other components, and a narrower scope of system knowledge.

Behavior: Collection of autonomously scheduled activities in service of an over-arching mission goal. Contains broad system knowledge.

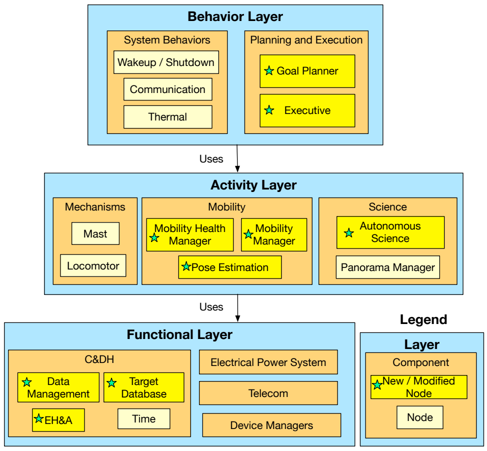

Figure 1: Self-Reliant Rover flight software architecture.

Activity: Coordinates function invocations to achieve some high-level spacecraft task. Encompasses knowledge local to the activity being managed.

Function: Primitive action required to achieve a single well-delineated spacecraft objective. Contemplates only highly-localized function-specific knowledge.

Following is a summary of the changes we are introducing for the Self-Reliant Rover approach. Subsequent sections will provide more details on the most significant changes.

Goal Planner: Generates onboard activity plans to accomplish mission goals. Improves resource utilization by synchronizing plans with in-situ vehicle resource knowledge. Responds to new goals identified by onboard autonomous science.

Executive: Executes plans generated by the Goal Planner and provides updates to facilitate re-planning.

Autonomous Science: Identifies science targets when the rover enters an unexplored area. Increases the scope of guidance that scientists can provide and deepens the integration with onboard planning, as compared with previous autonomous science on MSL [2].

Mobility Manager: Improves navigation by reasoning about terrain-dependent slip.

Mobility Health Manager: Increases the robustness of mobility activities and the scope of faults from which the rover can autonomously recover by leveraging model-based fault detection and isolation.

Pose Estimation: Maintains high quality position knowledge over long traverse distances via onboard global localization (a technique that previously required ground operator support).

Target Database: Facilitates communication about targets of interest among scientists, engineers, and onboard autonomous components by leveraging previous ground operations tools onboard.

Data Management: Provides queryable onboard data product access to autonomous components such as onboard science analysis.

EH&A: Provides onboard access to engineering, housekeeping, and accountability telemetry for use by autonomous reasoning components.

3 CAMPAIGN INTENT FOR OPERATOR GUIDANCE

A significant challenge to maintaining high rover productivity under reduced operator interaction is conveying operator guidance and objectives without requiring operators have up to date knowledge of the rover and its environment. Our approach is motivated by prior operations practice. In traditional operations, each planning cycle begins with a recapitulation of the current long term objectives of the mission presented in the context of the latest available rover state data [3]. The human operators assimilate all the various objectives, state data, and mission knowledge in order to synthesize a high quality plan that makes progress toward the goals while respecting limited rover resources such as time, energy, and data volume.

The team will typically have several high-level objectives to pursue. For example, during MSL's Pahrump Hills Walkabout campaign, the primary focus of the mission was to collect observations of exposed outcrop forming the basal layer of Mount Sharp [4]. This required driving the rover to several locations and acquiring high quality Mastcam and ChemCam observations selected locally at each stop.

Concurrently, the team also pursued a variety of supplementary objectives. During this campaign, Siding Spring (Comet C/2013 A1) would pass Mars closer than any other known comet flyby of Earth or Mars. The operations team thus incorporated comet observations into the rover plans. In addition, the team planned ongoing periodic observations to study clouds, dust devils, and atmospheric opacity. A wide range of recurring engineering activities also had to be included: instrument calibrations, telemetry collection, and system configuration management.

Importantly, the quality of the plan is not just a function of what activities are scheduled; it depends on how well they relate to the current objectives and to each other. Each individual outcrop observation was valuable, but understanding the geology of the region required accumulation of a variety of observations that were spatially distributed throughout the area. Periodic tasks such as atmospheric measurements and engineering activities had

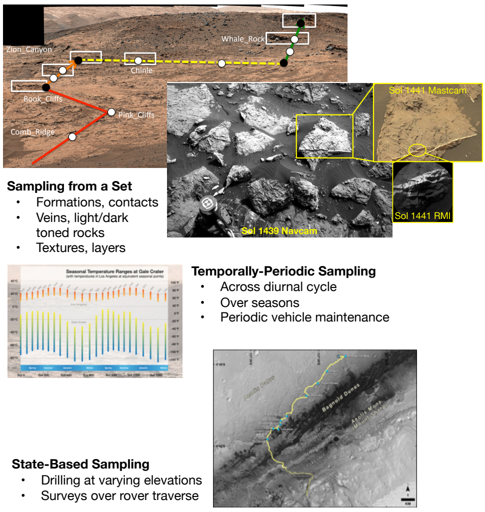

Figure 2: Summary of campaign intent types.

similar preferred temporal patterns that the team must try to match.

We developed the concept of *campaign intent* to convey such information to the rover so that it may generate its own prudent in-situ plans when human guidance is prohibitively delayed. Campaign intent specifies a set of goals for the rover and the relationships among those goals. We gleaned three initial types of campaign intent from MSL scenarios, as summarized in Figure 2:

Class sampling: Choose observation targets that best exemplify a particular feature (e.g. layering). Once identified, the targets form a goal set. Value typically accumulates with additional samples from the set, but eventually reaches a point of diminishing returns.

Temporally-Periodic sampling: Schedule goals to match a repeating temporal pattern (e.g. hourly). The preferred goal cadence typically allows at least some timing flexibility.

State-based sampling: Trigger goals based on the evolution of the rover/terrain state (e.g. at every 50m traveled). The state criteria is typically expressed as a preferred cadence with some flexibility.

3.1 Using Campaign Intent to Guide Planning

Our approach to plan generation is based on branch-and-bound search. Starting from the empty plan, each iteration of search expands a chosen partial plan into many possible successor plans (the branches). Each potential successor is scored and must exceed a running threshold of plan quality (the bound) in order to be retained for future expansion; otherwise it is pruned (along with all its descendants). Specifically, the optimistic maximum quality of any plan based on the candidate partial plan must exceed the pessimistic minimum quality prediction of all other candidates already considered. Plan

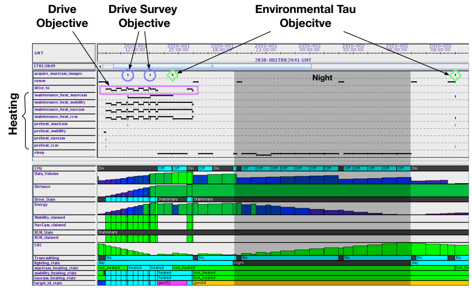

Figure 3: Example generated plan illustrating a long-range drive objective that was split up to support two different types of campaign objectives.

quality is evaluated as the degree of satisfaction of the campaign intents, which may be both priority tiered and utility weighted by the user. The frontier of un-expanded partial plans is periodically sorted by estimated final plan quality, yielding a hybrid of depth-first and best-first expansion order.

Partial plans are always expanded forward in time by appending one of the possible subsequent actions to the growing plan. The possible actions include mandatory goals (such as communication passes), auxiliary actions (such as sleep periods), as well as all the possible goals introduced by campaign intents. For temporal and state-based campaigns, this is just the next instance of the periodic goal, timed within its allowed cadence. For unordered goal set campaigns, each remaining un-attempted goal becomes a possible addition. In the limit, the search will thus evaluate (or justifiably prune) all possible combinations and orderings of campaign goals.

The complete search can be very time intensive, but is guaranteed to return an optimal plan according to the expressed campaign preferences. Even without running to completion, the search can return the best plan encountered so far. This anytime algorithm feature allows the rover to limit its planning time and proceed to be productive with a reasonable (but not provably optimal) plan. Minor plan perturbations during execution are accommodated by time-efficient repair strategies (for example, to shift actions forward after a small driving delay), while major disruptions (such as an insurmountable obstacle in a drive, or the injection of an entirely new goal) invoke a full replanning cycle so that all goals are reconsidered.

Figure 3 shows an example plan generated by the search algorithm. The planning model derives from the operational MSL activity model and features important mission aspects such as science campaign activities, communication windows, regenerative sleeping, and device heating.

The campaign objectives provided to the rover in this example include: a goal set campaign with a distant MastCam target (entailing a long-range traverse), a temporal campaign with recurring atmospheric opacity (tau) measurements every 3 hours, and state-based campaign with mid-drive survey actions after every 75 meters traveled. The resultant plan demonstrates how the planner synthesizes the campaign relationships to coordinate rover activity, including pausing the ongoing drive action to interleave other objectives.

3.2 Using Campaign Intent to Guide Autonomous Science

The system also leverages high-level campaign objectives to introduce additional in-situ goals based on scientist guidance. This improves rover productivity when the operations team does receive data about the rover's environment in time to select their own local targets for that day.

For example, scientists may be interested in remote-sensing composition measurements of a rock formation encountered previously and known to exist in a region the rover is approaching. The scientists can train a TextureCam [5] model to detect that rock formation by labeling examples in previous navigation camera images (Figure 4, left). The rover then runs that TextureCam model onboard to compute a probability map of locations in the new region that likely contain the rock formation of interest (Figure 4, center). The probability map can be used to select the best targets for measurement, as well as the likelihood that each measurement satisfies the scientific intent of characterizing the rock formation (Figure 4, right). Each proposed target becomes a new goal in the campaign set for the planner. The planner may also use the probability information to reason about the trade offs between the various generated goals.

4 SLIP-AWARE NAVIGATION

The Navigation systems equipped on the Mars rover missions, Mars Exploration Rover (MER) and Mars Science Laboratory (MSL), rely on the Grid-based Estimation of Surface Traversability Applied to Local Terrain (GESTALT) algorithm [6] to detect and avoid geometric hazards and the $\mathbf{D}^*$ algorithm [7] to plan global paths to goals. These methods have enabled operators to provide high-level autonomy goals to the rovers, increasing mission efficiency.

However, geometry alone is not sufficient to guarantee safe traverses on the surface of Mars in every environment. Both MER and MSL operators have experienced hazardous conditions due to otherwise geometrically benign terrain such as sand dunes, and small rocks. These hazards can create adverse conditions such as wheel slip, sinkage, and damage. When current rovers pass through these hazardous environments, operators control the rovers manually with slow, deliberate commands, resulting in a loss in efficiency. In response, this paper proposes a navigation system that can reason about geometry *and* terrain type to plan safe reliable paths to science targets and enable a larger role in autonomy for future Mars Rovers.

System Overview The slip-aware navigation system, highlighted in Figure 5, is built upon the GESTALT system [6] and contains the following components: i) stereo vision, ii) visual odometry, iii) traversability assessment, iv) terrain classification, and v) path planning. The input to system is a synchronized pair of stereo images from the rover's navigation cameras. Image data is sent to the OpenCV [8] block matching algorithm to obtain dense 3D information about the environment. In parallel, the left stereo image is sent to a speeded-up version of the Soil Property and Object Clasification (SPOC) [9] terrain classifier more suited for on-board computation requirements. This segments the image into three classes: i) sand, ii) soil, iii) flagstone. Both texture and depth information are then sent to the Jet Propulsion Laboratory (JPL) Visual Odometry (VO) method detailed in [10] to compute the relative motion between images. This information is the incorporated into the 3D map and assessed for both geometric and slip hazards in the traversability-assessment module. Geometric Hazards are assessed and mapped using the Morphin algorithm [6], a predecessor to the GESTALT method running on the Mars rovers To plan safe paths around geometry- and terrain-based hazards, we employ the RRT# sample-based planner [11] to make informed decisions on adding new samples using the computed geometry, terrain, and rover motion information.

Slip-Aware Planning Our navigation system plans paths on a map that builds upon the data structure detailed in [6]—an occupancy-grid map fitted to a local ground plane with point-cloud statistics. The slip-aware navigation system improves on this map structure by adding terrain information information for each point in the stereo point cloud. Point clouds are accumulated to compute geometry and terrain statistics at each cell in the map. To assess the traversability of the map at each cell, a plane the size of the rover is centered and fitted to the containing points. Each cell in the map contains the following information: i) maximum step-size, ii) roughness, iii) slope, and iv) terrain information. Terrain information comes in the form of a discrete probability distribution for the three terrain types of interest: soil, sand, and flagstone.

The slip-aware navigation system plans safe paths that avoids geometric- and terrain-based hazards by employing the sample-based planner, RRT# [11] and the traversability map to make informed decisions on expected wheel slippage. The sample-based planner constructs a random graph where vertices contain robot poses and edges link poses by vehicle-constrained motion primitives [12]. During planning, new vertices are considered as viable if they do not intersect with any geometric obstacles in the map (step-size or roughness). The cost of edges in the graph is a function of the motion primitive distance weighted by an expected slip profile for each

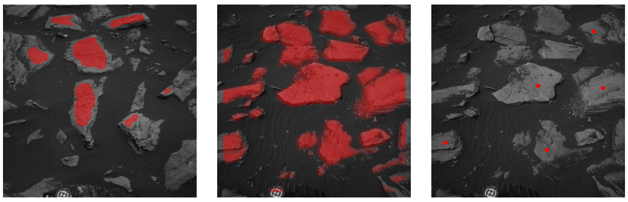

Figure 4: An example showing how scientists can use TextureCam to express intent to autonomously generate new goals on board. The left image shows hand-labeled regions of a geological formation of interest. The center image shows the estimated probabilities that regions in a new image are of the same formation, given a model trained from labels. The right image shows the top five software-selected locations for diverse observations of the rock formation, each corresponding to a new goal for the planning system.

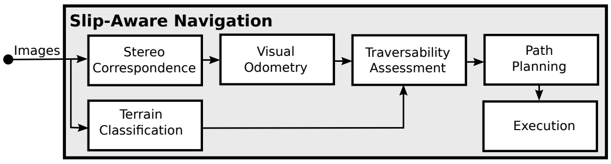

Figure 5: Illustration of the slip-aware navigation pipeline.

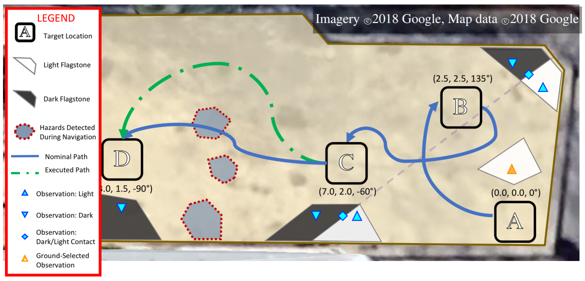

Figure 6: Overview of simulated mission area. Operator inputs include a specific target selection (orange) near starting area A along with only high-level campaign guidance for areas B, C, and D. Automated science analysis injects additional targets (cyan) during execution. The initial planned route (blue) is dynamically adjusted (green) to avoid unanticipated terrain hazards (red).

terrain type. Terrain slip profiles map slope to expected rover slip for a given terrain type. This planner furthermore takes into account direction of travel when adding a new sample.

5 ILLUSTRATIVE SCENARIO

The Self-Reliant Rovers system was demonstrated on the JPL Athena test rover within a mission scenario that explores the JPL mini-Mars Yard robotic testing facility. The primary science objective was to characterize the rock outcrop materials embedded in the sandy soil using the rover's mast-mounted cameras. The mission spans a period of limited communication with operators, so the rover must operate almost entirely autonomously in order to remain productive toward its high-level goals.

Figure 6 shows the overhead layout of the mission area, as might be available to mission planners from orbital imagery. The operations team selects several regions of interest (indicated by letters) from this coarse data, but is unable to identify specific targets or terrain obstacles beyond a few meters from the rover, for which the team has local imagery obtained from the rover. Previous local imagery allows the operators to set one precise outcrop target nearby the starting location at A. In prior operations, the team would have to be satisfied with filling the rest of the communication-limited period with various in-place tasks and perhaps one drive attempt toward the next area. Instead, using the Self-Reliant Rover system, the team can entrust the rover with enough campaign intent to continue conducting detailed science on its own.

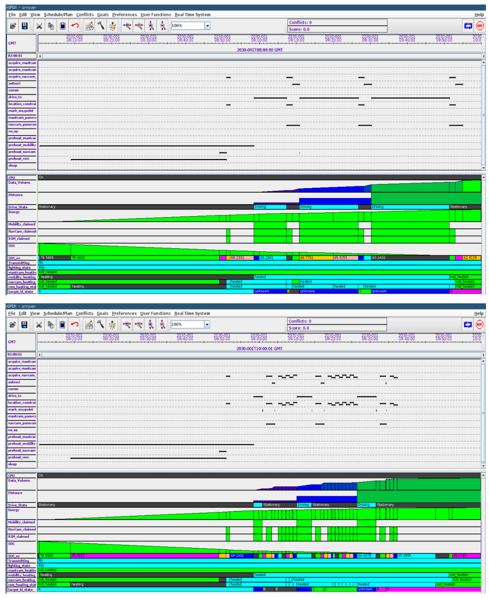

Figure 7: Initial generated plan and final as-executed plan for the simulated mission scenario. Many new targeted science goals are suggested at run-time by automated image analysis and then integrated into the schedule in service of science campaigns. Drive estimates are also updated during execution, thus correcting initial approximations.

First, the operators create a goal for each area of interest that entails driving to a specified vantage point in that area, acquiring a contextual wide-angle image, and then running the appropriate automated science algorithms. These survey goals become part of their own goal set campaign, and the planner will stitch together an optimal drive ordering to achieve as many as possible. In addition, the scientists create initially empty goal set campaigns for each of the desired outcrop observations (light flagstone, dark flagstone, and multiple-contact) at each area. The campaign intents provide guidance for the rover's autonomous science behavior by indicating the algorithms to perform and the types of follow-up observations to suggested based on the results. During subsequent automated analysis, the previously trained onboard science classifiers will inject their newly identified follow-up targets as goals into these campaign containers for consideration during replanning.

Scalable campaign satisfaction criteria are described as a utility scored range over the number of observations desired. The planner and automated science cooperate to identify the best candidate targets to include in the plan so as to maximize expected utility score. When a campaign cannot be minimally satisfied with available targets, it may be skipped over in order to include lower priority campaigns. Likewise, only the best observation targets up to the desired maximum for a campaign will be scheduled. In this demonstration scenario, campaigns request follow-up mast camera imaging of the 2-5 best outcrop specimens in each category at each location.

Several additional relevant campaign types were demonstrated in separate scenarios. The operators can specify ongoing temporal periodic campaigns; for example, visual atmospheric opacity (τ) measurements every 20±2 minutes. Mandatory downlink relay communication passes can also be enforced at specific times in the schedule, representing a exogenous orbiter overflights.

All of the various goals are provided to the rover at its morning communication pass at the start of the mission scenario. Thereupon, the onboard planner generates a plan to image the specifically requested target near A, and then travel in turn to B, C, and D to conduct survey observations (Figure 7, top, and Figure 6, blue path). The plan adheres to all standing rover resource limits (such as battery energy and data volume), as well as incorporating any required heating (such as needed for instruments or mobility mechanisms).

The actual path driven by the rover undergoes refinement by the onboard terrain classification and autonomous navigation so as to best avoid geometric obstacles. Due to a lack of terrain diversity and slopes in the testing environment, the slip avoidance aspect of the planner was disabled.

Depending on terrain, drives may also perform better than expected by the initial approximation. Diversion delays and expeditious travel cause minor perturbations to the plan, which are accommodated by an agile plan repair strategy that shifts actions within some threshold as long as they still meet their requirements.

Figure 8: Automated detection of geologic formation contact in a survey image (top, contacts highlighted in red) triggers follow-up detailed imagery of the contact area (inset).

On arriving at B, and later C, the rover acquires the requested contextual images and analyzes them using the onboard science detectors. In turn, the analysis software identifies both light and dark flagstone outcrops, as well as contact between the two (Figure 8, top, with contact areas highlighted in red.) These specific follow-up targets are then automatically injected as new goals in their respective campaigns, and a replanning cycle is initiated. The planner's updated solution includes each of the newly suggested observations, which are duly collected (Figure 8, inset) before proceeding to the next area.

Upon driving toward D, the rover's automated terrain classification identifies a major obstacle, and the navigation system must divert significantly. The planner assimilates updated drive estimates from the navigation engine to ensure that the plan can accommodate the delay without conflict. After planning a safe path around the observed obstacles and eventually reaching D, the system once again identifies flagstone features and conducts the requested follow-up observation. At this point the mission period ends.

As seen in the final plan (Figure 7, bottom), the productivity benefits of additional onboard rover autonomy are evident even within the limited scope of this demonstration scenario. Traditional operations would have accomplished just one initial outcrop observation and a first drive.The combined autonomy of the Self-Reliant Rover system produced three survey panorama images throughout the mission area, toured several unexpectedly difficult terrain routes, and accrued fifteen additional targeted outcrop observations. The Self-Reliant Rover system also allows the rover to incorporate periodic objectives into its generated activity plans. Overall, the scenario demonstrates the ability of the Self-Reliant Rover approach to increase mission productivity.

6 RELATED WORK

Shalin, Wales, & Bass conducted a study of Mars Exploration Rovers operations to design a framework for expressing the intent for observations requested by the science teams [13]. Their focus was the use of intent to coordinate planning among human operators and the resulting intent was not captured in a manner that would be conducive for machine interpretation. Our approach codifies some of the fields in their framework in a way suitable for the rover. In particular, the authors defined a "Related Observations" field as a way for scientists to identify relationships among different observations, which need not be in the same plan. Our work on campaign intent can be seen as a way of defining a specific semantics to these types of relationships to facilitate reasoning about these relationships by the rover.

Their framework also includes information that we agree is essential for effective communication among operators but that we do not currently express to the rover. For example, the "Scientific Hypotheses" field is used to indicate what high-level campaign objective is being accomplished by the requested observation. We are not yet providing these higher-level campaign objectives to the rover, though it is an interesting area of future research.

There are some similarities between our campaign definitions and those used for Rosetta science planning [14]. Both use campaigns to express requests for variable-sized groups of observations with relationships and priorities. Rosetta plans covered much longer time periods (e.g. weeks) and required more complex temporal patterns, such as repeating groups of observations. But observation patterns were primarily driven by the predictable trajectory of the spacecraft, allowing relationships to be expressed as temporal constraints. This is not sufficient for rovers, where many observations are dictated by the rover location and surrounding terrain, and the duration of many activities cannot be accurately predicted. State-based and goal set relationships more accurately represent some of the science intent found on surface missions.

There have been a variety of autonomous science systems deployed or proposed for rovers including the AEGIS system running on the Opportunity and Curiosity rovers [2], and the SARA component proposed for an ExoMars rover [15]. These systems allow the rover to identify targets in its surroundings that match scientist-provided criteria. The introduction of campaign relationships broadens the scope of the type of guidance that scientists can provide these systems, allowing scientists to express the amount of observations they would like for their different objectives along with the relative priorities of the high-level objectives.

There have been several integrated rover systems with similar objectives to our work including ProvisScout [16], Zoe [17] and OASIS [18]. The ProViScout project has similar objectives to our work [16]. These systems It include autonomous science capabilities to enable onboard identification of science targets. Similar to our approach, they select follow-up observations for identified targets and submits these requests to an onboard planner to determine if there are sufficient resources to accomplish these new objectives. The campaign intent concepts we have developed would also be applicable to ProViScout as a way to increase the expressivity for providing scientist intent to the rover.

The Mars 2020 mission is planning to incorporate onboard scheduling to improve resource utilization of the rover [19]. Similar to the Self-Reliant Rover approach, the use of onboard scheduling is intended to allow the Mars 2020 rover to use current vehicle knowledge when generating schedules to accomplish mission objectives. This will reduce the loss of productivity that results from the difficulty in predicting how much resources (e.g. time and energy) activities will consume. The Self-Reliant Rover approach is addressing additional productivity challenges by improving the ability of rovers to identify their own objectives, to incorporate a richer set of guidance from operators and to reason about slip hazards as it navigates.

The navigation system presented in this paper is most similar to the system presented in [20]. They propose a system with the same high-level machinery: i) a GESTALT-based vision pipeline, ii) a terrain classifier, and iii) a slip-aware planner. However, their system is not capable of making decisions based on direction of travel. When direction of travel is not considered, then the system is forced to make more conservative plans. An example is if the rover is planning a path on a steep slope containing soil, it might be too dangerous to drive up the slope due to expected slippage, but driving downhill would be safe.

7 CONCLUSIONS

We have presented an approach for increasing the authority of autonomous rovers to increase mission productivity. Our approach includes the ability for ground operators to provide guidance to the system without requiring up to date knowledge of the rover's state and its surroundings.

We have implemented a prototype of this approach on the Athena test rover. Over the next year we will be conducting mission-relevant, multi-sol scenarios with the rover at the JPL Mars Yard to evaluate its ability to support productive operations with limited ground-in-the-loop interactions.

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