

# Self-Reliant Rover Design for Increasing Mission Productivity

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## 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.

## 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

## 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 (Weiss 2013). Figure 1 provides an overview of this architecture and the changes we are introducing.

The Jet Propulsion Laboratory (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.

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

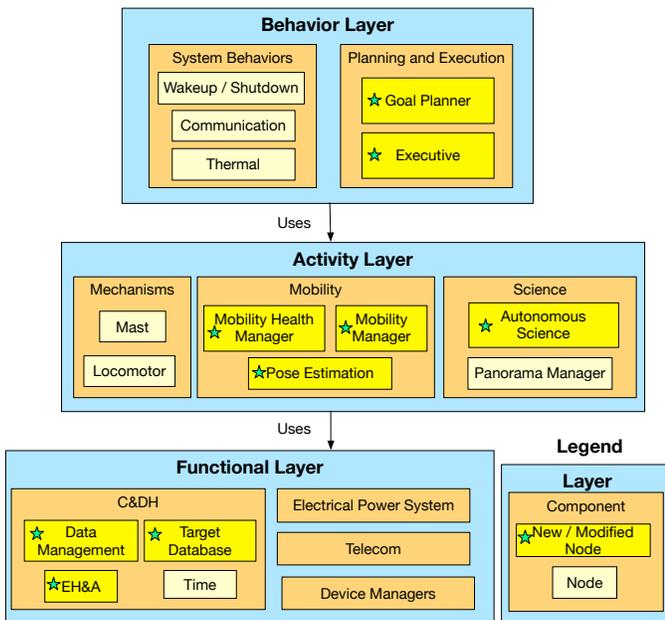


Figure 1: Self-Reliant Rover flight software architecture.

**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 (Francis *et al.* 2017).

**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, house-keeping, and accountability telemetry for use by autonomous reasoning components.

### 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 (Chattopadhyay *et al.* 2014). 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 Walk-about campaign, the primary focus of the mission was to collect observations of exposed outcrop forming the basal layer of Mount Sharp (Gaines *et al.* 2016). 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 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 accumu-



## 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 (Thompson *et al.* 2012) 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.

## 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 (Goldberg, Maimone, & Matthies 2002) to detect and avoid geometric hazards and the  $D^*$  algorithm (Stentz & Mellon 1993) 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 (Goldberg, Maimone, & Matthies 2002) 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 (Bradski 2000) 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 Classification (SPOC) (Rothrock *et al.* 2016) 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 JPL Visual Odometry (VO) method detailed in (Howard 2008) to compute the relative motion between images. This information is 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 Morphing algorithm (Goldberg, Maimone, & Matthies 2002), 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 (Arslan & Tsiotras 2016) 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 (Goldberg, Maimone, & Matthies 2002)—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 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# (Arslan & Tsiotras 2016) 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 (Pivtoraiko, Nesnas, & Kelly 2009). 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 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.

## Model-Based Health Assessment

The autonomous science scenario discussed in previous sections is only practical under two strong assumptions: First, that the rover protects itself from any problems during auto-generated activities; and second, that the rover can reliably detect and recover from problems that are routine but

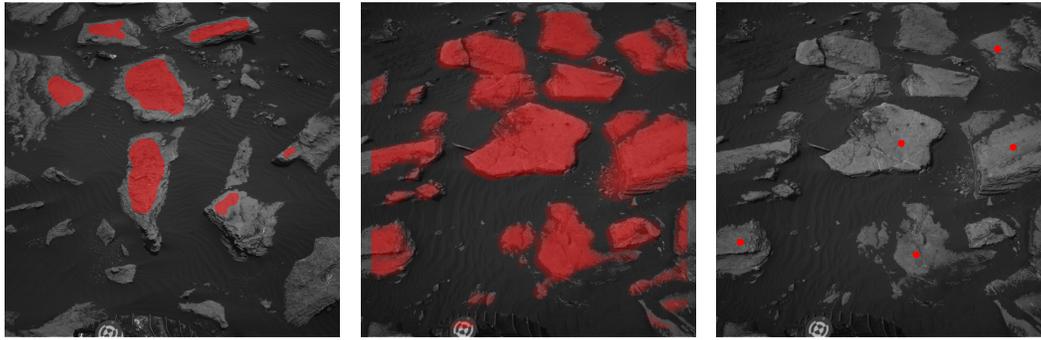


Figure 4: An example showing how scientists can use TextureCam to express intent to autonomously generate new goals on board. The left image shows hand-labeled regions of a geological formation of interest. The center image shows the estimated probabilities that regions in a new image are of the same 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.

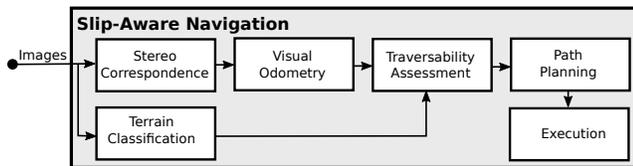


Figure 5: Illustration of the slip-aware navigation pipeline. This navigation system uses both geometry and texture from stereo images to map and assess hazards to the rover and plan safe paths in challenging environments with high slip risks. This will allow rover operators to plan longer autonomous traverses in difficult terrain.

currently require ground-in-the-loop resolution. Both challenges exceed the current state of practice for rover health assessment. We must assume an autonomous rover will have only limited knowledge of the terrain due to its more aggressive exploration, and thus the autonomous rover will be unable to avoid some hazards that a traditional rover would bypass. Existing rover fault protection can be elaborate – Mars Science Laboratory (MSL), for instance, has over 1,000 distinct fault monitors – but is defensive in nature, aimed at maintaining rover safety and preserving capability rather than ensuring efficiency of operations.

In current operations it is not unusual for even a routine activity (such as a drive) to “fault out,” i.e., halt prematurely or exit with errors that requires ground analysis before resuming operations. These are typically benign, caused by factors such as slower progress than expected or incorrect assumptions about activity timing. Nonetheless, the Self-Reliant Rover must be able to discriminate recoverable problems from more serious ones, it must solve the simpler problems without ground input, and it must do both reliably.

It is clear that we are unlikely to achieve this by simply expanding the scope of fault protection. Instead, to compensate for uncertainty in the environment, the plan, and in the rover performance itself, we turn to model-based methods and reasoning systems. The Self-Reliant Rover prototype incorporates Model-based Off-Nominal State Identification

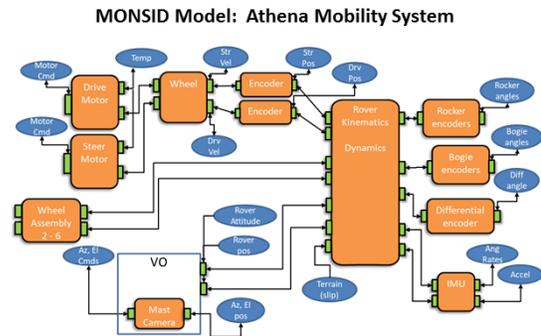


Figure 6: MONSID model of Athena mobility components

and Detection (MONSID) (Kolcio & Fesq 2016), which analyzes command and sensor data in real-time to construct an estimate of system health.

MONSID utilizes a simplified physics model comprised of a network of numerical constraints, describing the physical laws and relationships between sensed and internally-computed parameters. The model also relates these constraints to physical or logical components of the host system, allowing inconsistencies found to be linked to their root cause. MONSID was applied to an example rover electrical power subsystem in a previous experiment (Kolcio, Fesq, & Mackey 2017), illustrating the suitability and unique advantages of the approach while exposing model details and algorithm behavior.

For integrated testing with Athena, MONSID concentrates on the mobility systems and associated sensors. A summary of the MONSID model is shown below in 6.

In the diagram above, orange boxes represent rover components or pseudocomponents that aggregate different state variables. Blue ovals indicate command or sensor values, used to enable or verify computation of system state variables. Connections between components as indicated by ports (green boxes) represent constraints, evaluated separately.

rately in each direction.

Each of the six wheels incorporates separate steering and drive motors, while the wheel assembly interacts with the controller via a pair of position encoders. Rover position and orientation is provided by visual odometry, analyzing images captured by Athena's mast-mounted cameras, and a notional Inertial Reference Unit (IMU). Additionally, the model supports variation in rocker and bogie position, as reported by four angle sensors. Note that in the current implementation both IMU and suspension sensors are not present.

During execution MONSID must detect faults and distinguish which are autonomously recoverable in a manner that other autonomy components can interpret. To support our evaluation, the Athena team has developed a fault injection capability enabling us to simulate drive and steering motor failure, failure of on-board controllers, and failure of mobility sensors. The most relevant cases to the autonomous rover science scenario can be summarized as follows:

**Detect and classify recoverable mobility faults:** If a drive is interrupted by an unexpected event, determine whether this is terrain-induced or caused by mechanical failure, and whether the rover should autonomously retreat and avoid the problematic terrain.

**Recognize errors in terrain knowledge:** If drives complete but leave the rover far from its expected position, determine whether the problem is caused by mechanical failure, sensor failure, or incorrect assessment of terrain. In the latter case, attempt to recover terrain knowledge by comparing to alternate models of terrain behavior.

**Identify emergent, unknown, or surprise behavior:** A significant hurdle to adoption of autonomy technologies in general is the persistent risk of unexpected behavior in the system leading to an unpredictable response. However, due to its reliance upon physical principles instead of purpose-built monitors, model-based health assessment is often capable of detecting and correctly classifying even novel system behavior.

An example of the last class of behavior was observed by the Athena team in early 2018, when driving up a steep slope led unexpectedly to one of the front wheels rising off the surface. We quickly replicated this behavior in our testing, finding it was caused by unexpectedly high traction in Athena's center wheel coupled with slippage of the rear wheel. This resulted in the center wheel driving forward relative to the rover as a whole, rotating the bogie in the process. A brief summary of this behavior is shown in 7.

This behavior is interesting because, while undesirable, all individual rover components are operating in familiar and acceptable ways. The root cause is instead a violation of a more fundamental assumption about the rover, namely the rover wheel geometry is changing while on flat terrain. These assumptions are incorporated into the MONSID constraints, and as a result, the novelty of this situation is detected without difficulty, despite the fact that this behavior had gone unnoticed after years of testing and experience with Athena.

Unlike the other types of faults, it is likely that we would halt operations after observing this for the first time in flight

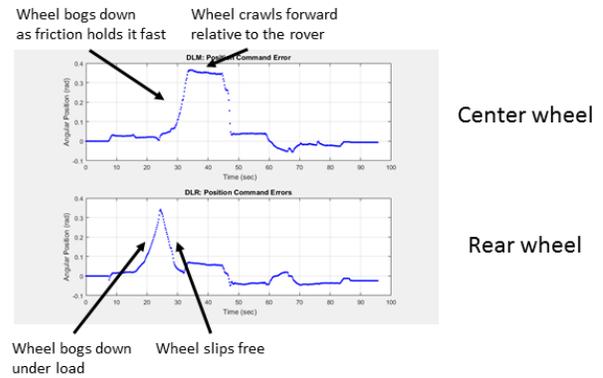


Figure 7: Athena drive position error during unusual "wheelie" behavior

to permit thorough analysis of newly revealed design vulnerabilities. MONSID's responsibility in this case ends with detection and classification as a non-recoverable event, however MONSID also provides diagnostic information to assist in event analysis. In this case the fault is correctly isolated to the center and rear wheels instead of any control fault, or any fault in the wheel that actually rises from the surface.

## Global Localization

One of the key goals in improving autonomy for mobility is extending the distance the rover can drive per sol. Localization errors accumulate as a function of driving distance, however, due to drift in visual odometry and the integration of inertial measurements. The magnitude of this error depends on the terrain, but can be on the order of 5% of the drive distance. For MSL operations, the typical drive distance is on the order of 30m, resulting in fairly small drift in position estimate that could be several meters.

For MSL, this drift is corrected manually by visual alignment of navcam imagery to orbital HiRISE imagery. To estimate the alignment, a mosaic of navcam stereo images are taken to cover a full panoramic around the rover. These images are then orthographically projected and salient surface features are manually tie-pointed to compute a correction offset.

The self-reliant rover design utilizes both longer drives as well as multi-sol operations without the involvement of ground operators to perform these corrections. To achieve this, a similar alignment method is used in an automated manner onboard the rover. Instead of keypoint tie-pointing, the images are aligned using a matching criteria on both the image intensities and the elevation map. Both the surface and orbital images are orthographic projections, created by projecting the image onto the elevation map using HiRISE DEMs (digital elevation models) for the orbital images, and stereo disparity from the surface navcam images. The orbital image products are georeferenced and stored on the rover.

The matching criteria for the imagery uses mutual-information, or relative entropy, between the images (Ansar & Matthies 2009). This measures the statistical dependence

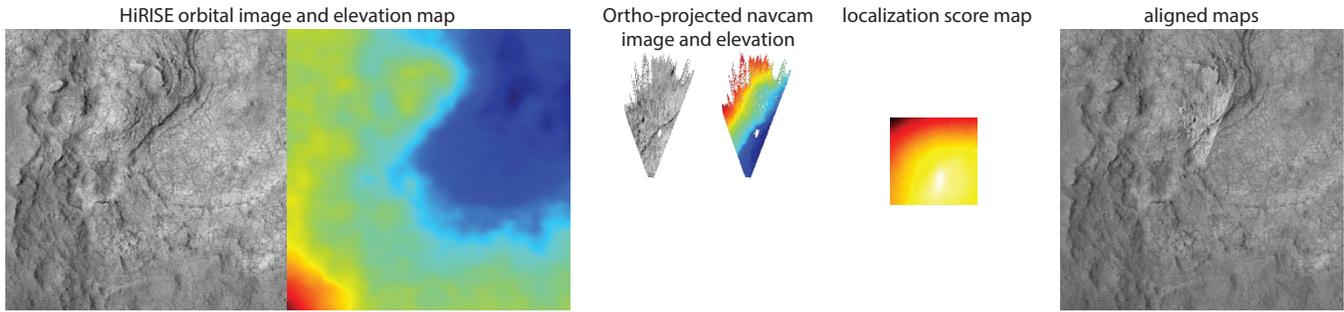


Figure 8: Global localization utilizes automated alignment of navcam image and elevation maps to onboard orbital maps.

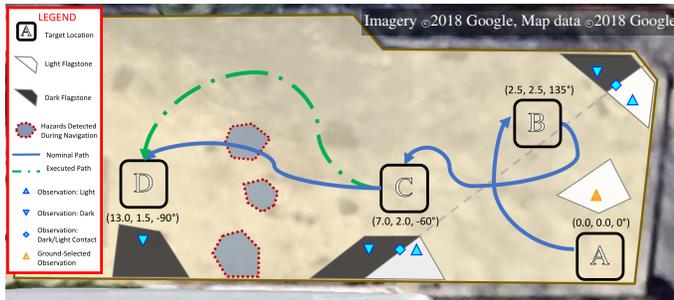


Figure 9: Overview of simulated mission area. Operator inputs include a specific target selection (orange) near starting area A along with only high-level campaign guidance for areas B, C, and D. Automated science analysis injects additional targets (cyan) during execution. The initial planned route (blue) is dynamically adjusted (green) to avoid unanticipated terrain hazards (red).

between corresponding pixels of a candidate alignment. Mutual information is used instead of more conventional correlators such as SAD or SSD for robustness to varying conditions from when the orbital image was acquired such as lighting or surface changes. The elevation map alignment uses a conventional SSD correlator. The overall matching score is simply a weighted sum between the image and elevation scores. The maximum drift of the position estimate is largely bounded, and the alignment search can be performed using a conventional sliding window approach.

### 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 9 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 inter-

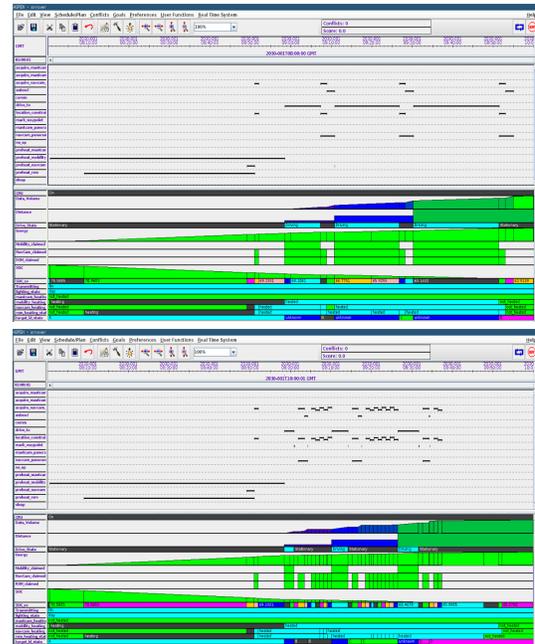


Figure 10: Initial generated plan and final as-executed plan for the simulated mission scenario. Many new targeted science goals are suggested at run-time by automated image analysis and then integrated into the schedule in service of science campaigns. Drive estimates are also updated during execution, thus correcting initial approximations.

est (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.

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 ( $\tau$ ) measurements every  $20 \pm 2$  minutes. Mandatory downlink relay communication passes can also be enforced at specific times in the schedule, representing an 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 10, top, and Figure 9, 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.

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



Figure 11: 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).

between the two (Figure 11, 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 11, 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 10, 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.

## Related Work

Shalin, Wales, & Bass, (2005) conducted a study of Mars Exploration Rovers operations to design a framework for expressing the intent for observations requested by the science teams. 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.

Mali (2016) views intent as a means for a user to place constraints on the types of plans a planner is allowed to produce such as only generating plans that have at most one instance of a class of actions or that plans must limit the use of a particular action. The primary role of our use of intent is to allow the planner to assess the value of achieving a given set of goals. However, some of our campaign intent does imply constraints and preferences on how, or more specifically, when goals are accomplished. For example, the periodic campaign intent specifies a timing relationship among goals and a preference on how close to comply with the desired timing.

There are some similarities between our campaign definitions and those used for Rosetta science planning (Chien *et al.* 2015). 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 (Francis *et al.* 2017), and the SARA component proposed for an ExoMars rover (Woods *et al.* 2009). 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 P<sub>RO</sub>ViScout (Paar *et al.* 2012), Zoe (Wettergreen *et al.* 2014) and OASIS (Castano *et al.* 2007). The P<sub>RO</sub>ViScout project has similar objectives to our work (Paar *et al.* 2012). These systems 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 P<sub>RO</sub>ViScout as a way to increase the expressivity for providing scientist intent to the rover.

There is an active area of research in intent recogni-

tion (Sukthankar *et al.* 2014). The general goal of this area is to identify the objectives of other agents (human or otherwise) from observations of the agents’ actions. In contrast, in our work, it is acceptable for users to explicitly identify their intent, rather than require the system to attempt to infer intent. Indeed, there is interest in the operations team to clearly document their intent for the purpose of communication among teams and as a record of what activity was planned for the rover and why. As such, rather than try to infer user intent, our objective is to increase the expressivity of the rover’s interface in order to more closely reflect mission intent.

The Mars 2020 mission is planning to incorporate on-board scheduling to improve resource utilization of the rover (Rabideau & Benowitz 2017). 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 (Helmick, Angelova, & Matthies 2009). 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.

## 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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