PERSIM: PERCEPTION FOR PLANETARY PROSPECTION AND INTERNAL SIMULATION

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ABSTRACT

For planetary robotics autonomous prospecting, robust, long-term navigation becomes crucial. The goal of the research project PerSim is to develop technology to address some of the challenges of *active perception for resource identification* and *long-term navigation strategies* in an integrated architecture. The fist assessment addressed autonomous selection of regions for inspection, combined arm-base approach, close range data acquisition and categorization of the acquired spectral data using Deep Learning. Furthermore, autonomous navigation including potential failure prediction and avoidance are also scoped. The following targets are pursued in the second assessment: an internal simulation to enhance the system safety and provide means for autonomous onboard safe testing, an episodic memory representation to serve as basis for the implementation of long term adaptation and finally a repertoire of behaviors to enable different motion modalities. The paper provides insights on the approaches and initial results.

Key words: Planetary Exploration; In-Situ Resource Utilization; Robot Autonomy.

1. INTRODUCTION

Technologies for identifying space resources will play a very important role in the future Moon and Mars missions. In this context, the capabilities of planetary exploration robots will become crucial for the discovery, collection and transportation of natural resources to Earth.

Resource Characterization (RC) is an essential prerequisite for efficient In-Situ Resource Utilization (ISRU) in order to secure and extend planetary missions and its significance was presented in [23]. Another advantage of RC technology development comes from the implementation of innovative scientific advancements to space exploration.

To evaluate the contributions in PerSim, two robotic platforms with similar mechanical characteristics are being used: Asguard IV[1] and Coyote III [29] (1). These are examples of hybrid rovers, where the advantages of wheeled and legged locomotion are combined. The rimless wheels allow the rover to overcome larger obstacles than normal wheels would. On the other hand, the mechanism is not as complex as an articulated leg, reducing the points of failure and the complexity associated to the control. One of the challenges that these systems pose is the minimization of vibrations on the rover body due to the impact timings of the wheels, specially on non-deformable surfaces. One main difference between Asguard IV and Coyote III is the arm that can be attached to Coyote III. On the end effector of such arm is planned to install a camera module incorporating 3D and hyperspectral imaging for close range resource analysis.

The goal is to develop integrative software modules that create a highly realistic representation of the environment with data relevant for RC gathered autonomously by a planetary rover. This data will help identify the mineralogical composition of materials such as stones, regoliths, water or ice. In particular close range 3D and hyperspectral measurements are targeted since these can provide higher precision localization of desirable resources than orbital data.

(a) Asguard IV (b) Coyote III

Figure 1: Rovers used in the project to test the components (photos by Thomas Frank and Florian Cordes, DFKI)

Multi-Level Surface Maps (MLS) for autonomous navigation are generated based on the environment represen-

[1]Asguard IV: `https://robotik.dfki-bremen.de/en/research/robot-systems/asguard-iv`

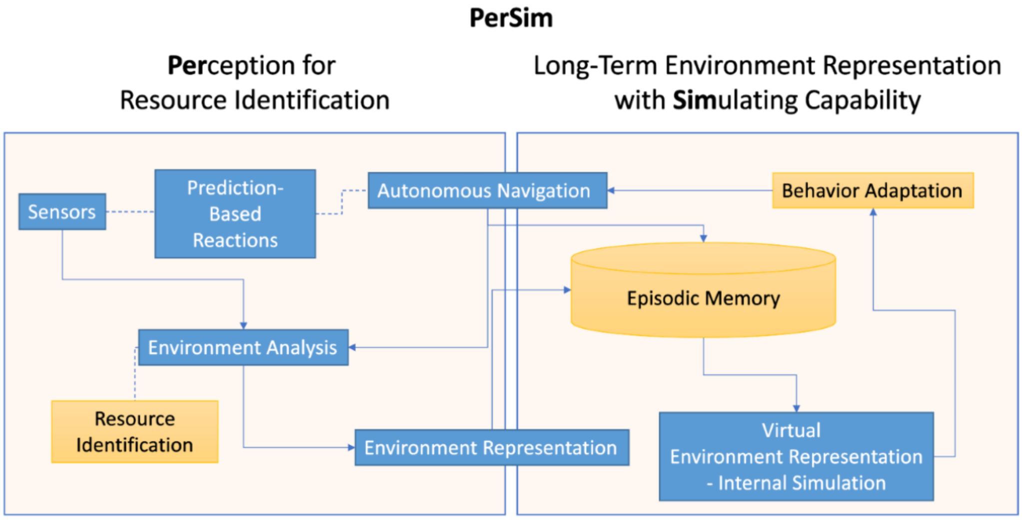

Figure 2: PerSim architecture overview.

tation [32]. In addition, a more detailed version of the MLS, which includes surface inclinations, is used to instantiate *Internal Simulations*. Another goal is to leverage such virtual environments on-board to enable the navigation software to foresee as precisely as possible the effects of potential actions. This will both enhance the safety in critical autonomous operations and minimize the risk when using learning approaches. Finally, the navigation experiences are stored in an *Episodic Memory* as a foundation to support the long-term learning techniques. A graph representation, currently in its first version, is used for recurring situations.

Previous research [24] has primarily focused on the importance of ISRU in space exploration and introduces RESOLVE, an innovative rover sensor/sampler concept designed to explore potential resources. The work by [16] addressed a cooperative multi-robot solution developed for National Aeronautics and Space Administration (NASA)'s Space Robotics Challenge Phase 2, focusing on the autonomous operation of robots for lunar resource utilization. It underscores the potential of such systems for lunar missions while addressing challenges related to mobility, localization, and coordination. For the "Commercial ISRU Demonstration Mission Preparation Phase" of the European Space Agency (ESA), the work by [33] emphasizes the importance of robot-assisted characterization and potential resource extraction and utilization from lunar surfaces. A team of legged robots equipped with advanced locomotion, perception, and measurement capabilities was introduced to successfully conduct missions in challenging planetary analog environments [1]. This technology showcased the use of mobile manipulation using legged robotics for RC and exploration. Most recently, the Indian Space Research Organization (ISRO), with their Chandrayaan III mission [11], demonstrated RC using a rover equipped with a spectrometer and spectroscope, allowing to determine the composition of elements in the vicinity of the landing area.

The project PerSim will develop and evaluate software components that pursue an increase in the degree of autonomy and reliability of navigation for planetary rovers. This includes components to: 1) control rimless rovers based on its specific dynamic models, 2) avoid hazards such as tip overs through terrain identification and tailored prediction-based approaches, 3) bring maturity and system independence to existent mobile manipulation and 4) investigate into long term adaptive capabilities. In addition, modules that enable strategies for RC as part of ISRU are pursued. These include RGB-Image based rock detection and close-range hyperspectral data characterization for material identification. These different contributions will be integrated into a main algorithm designed for the scenario of prospecting a target region. This paper presents the architecture and algorithms under development and the results from the first two outdoor tests.

2. ARCHITECTURE DESIGN

From a structural perspective, the diagram in Figure 2 shows a simplified overview of the components and connections that form the architecture. The components displayed in blue have been already developed for similar scopes in previous projects but they require adaptations for the rovers and scopes of this project, e.g. training of new models. The modules pictured in yellow are new.

From the behavioral perspective, the diagram in Figure 3 shows the final activities integrated as pursued by end of the project. The described cycle of activities represent the main algorithm in which the different modules will be integrated to address the scenario of prospecting a region on a planetary surface. The pursued activities can be divided into two main cycles: the exploration of an area as long as energy is available and the acquisition of the most relevant close range sensor data in the visible area.

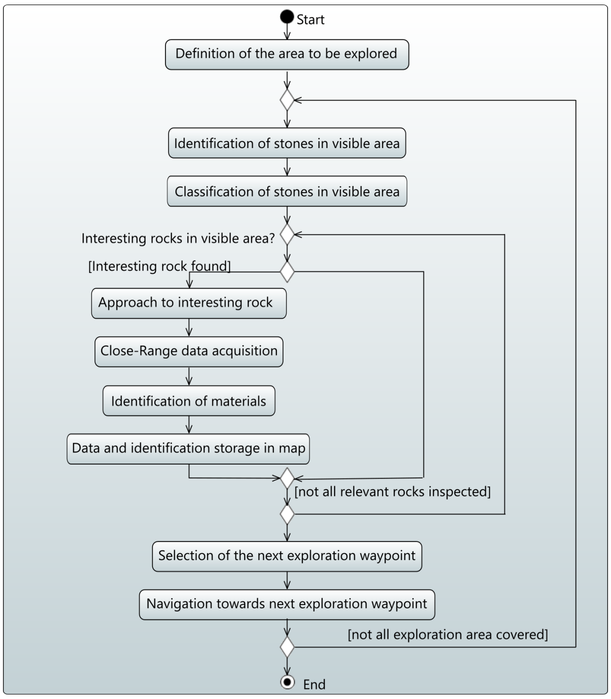

Figure 3: Proposed activities for the autonomous prospecting of a region of a planetary surface.

2.1. Resources Identification

The resource identification subsystem encompasses three primary objectives. Firstly, it aims to identify objects of potential interest in the context of planetary exploration with a specific focus on rocks. Secondly, it coordinates manipulator and rover motions designed to approach these objects autonomously. The third and final goal is to employ a hyperspectral camera mounted on the rover's end effector to acquire and classify the mineral composition of these rocks.

Rock Detection On the task of object identification, the goal is to implement a Neural Network (NN) that segments rocks from the planetary landscape. A scene segmentation Convolutional Neural Network (CNN) architecture was selected that is good for this task based on the U-net framework implemented by [21]. This network is a modified version of a fully CNN consisting of encoding and a decoding paths. The first repeatedly applies two 3x3 convolutions, a Rectified Linear Unit (ReLu), and a 2x2 max pooling operation. These operations progressively reduce the spatial dimensions of the input image to help extract high level features and capture contextual information. The second performs a symmetric set operations as the encoding path in an inverse manner. This up-sampling allows the network to use select details from the encoder path while recovering spatial information. Spatial recovery is also performed via the skipped connections that connect the encoder to decoder path and supports in preserving localization details in the image.

In addition, images from the Devon Island Navigation dataset [10] were selected to train the network. This

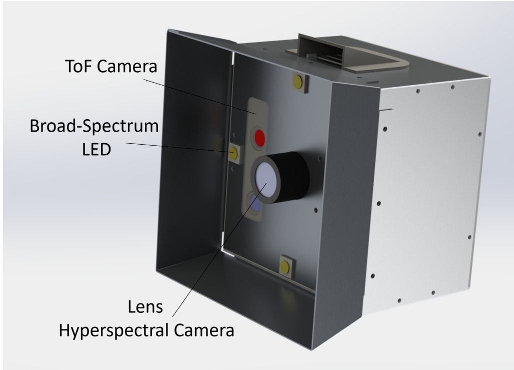

Figure 4: Camera module with hyperspectral camera, RGB+ToF-camera and wide-emission range LEDs.

dataset contains rover traverse data including stereo imagery. The images have captured many areas with vegetation-free planetary-analogue terrains with rocky canyons, boulder and sand fields with diverse topography.

Training the networks on these images will allow for the real-time rock detection as the rover follows its navigation trajectory. Subsequently, the locations of these rocks of interest will be recorded based on specific attributes, such as size, texture or shape. These still need to be evaluated for accuracy. The subsequent section provides an in-depth description of these sensor systems used for this purpose.

Sensors A camera module as shown in Figure 4 is developed. It contains a hyperspectral camera (Ximea SSM5x5) which provides 409×217 pixels with 24 bands in wavelengths between 667 and 947 nm, together with a wide emission range LED light source and sun shades to reduce the influence of external light sources. Additionally, a combined RGB and Time-of-Flight (ToF) camera (Vzense DCAM710), provides 3D spatial data corresponding to the hyperspectral data. A computation device (NVIDIA Jetson Xavier NX) makes

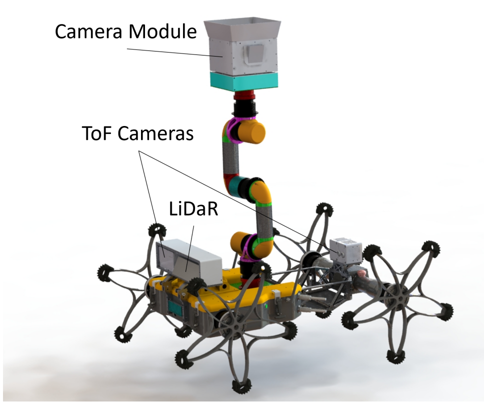

Figure 5: Placement of camera module (Fig. 4) and additional sensors on Coyote III.

the module almost self-contained, requiring only power and data connection to the rover's manipulator arm via an Electro-Mechanical Interface (EMI) [34]. The EMI also allows reusing the module with other robots.

The rover has a solid state Light Detection and Ranging (LiDaR) sensor at the front (Velodyne Velarray M1600) and one combined RGB and ToF camera each at the front and rear (Vzense DCAM560C Pro). These are used for mapping and navigation and the cameras also for the identification of rocks of interest. A complete rendering of the sensor payload on Coyote III is shown in Figure 5.

Mobile Manipulation Constraints are imposed on the manipulator arm's workspace by the integration of multiple sensor attachments, the rimless wheel design, and the free rotation joint for the rear axle of the Coyote III robot [28]. These constraints are encountered in conjunction with the complex environments during planetary exploration characterized by unstructured terrain and obstacles. The importance of a motion planning system that prioritizes both robustness and optimization to ensure mission safety is emphasized by these limitations. Thus, the need of a combined manipulator arm and rover motion planner becomes evident when these factors are considered.

Various mobile manipulation libraries were evaluated, including DFKI's in-house motion planner, the ADE motion planner [17], and the Multi-staged warm started motion planner [18]. After careful consideration of the project's specific demands and prerequisites, the ADE motion planner was selected as the optimal solution. This choice is rooted in the planner's inherent capacity to find an optimal base trajectory using an optimization-based Fast Marching Method (FMM) approach [26] and a robust arm trajectory effectively circumventing collisions.

To achieve this, a Digital Elevation Model (DEM) is generated from sensor data, complemented by the derivation of auxiliary maps, including slope maps, traversable maps, and cost maps. The Frontal Approach Cost Editing (FACE) algorithm, as developed in [17], is employed for the generation of precise base orientation control and to reduce unnecessary maneuvers. This algorithm modifies the cost map to align the base heading with the last waypoint towards the sample.

In this context, the determination of arm motion is equally vital, and a 3D cost tunnel is first constructed around the base trajectory. Then, the arm motions are generated using a 3D FMM applied within the 3D cost tunnel. Collision avoidance in arm movements is ensured by this approach.

For every base waypoint, a suitable waypoint of the arm trajectory is created, and the joint configuration is determined using inverse kinematics. Options to determine when the arm movements should start with respect to the base, namely 'beginning deployment,' 'end deployment,' and 'progressive deployment,' are also provided by the planner. Smoother arm motions are generated by the progressive deployment option as the motion of the arm is distributed equally along the base trajectory. Finally, proper tracking of the base path and arm joint profile is ensured by a coupled trajectory controller.

Figure 6: The dataset is comprised various examples of igneous, sedimentary and metamorphic rocks and mineral rocks.

Hyperspectral classification The precise execution of the mobile manipulation is essential for Hyperspectral Image (HSI) classification. Incorporating HSI will generate composition-rich representations of the navigated environment valuable for the prospecting of a planetary landscape.

To achieve HSI classification, a dataset will be built from a collection of mineralogical samples as shown in Figure 6. This collection of samples is composed of 40 various examples of igneous, sedimentary and metamorphic rocks. It also includes 40 of the most important basic materials for the production of pure metals and alloys.

Recent advancements in HSI classification for mineralogical composition have shown shown the advantage of Deep Learning (DL) over traditional Machine Learning (ML) methods in some classification problems [27, 13]. Notably, within the domain of HSI classification, studies such as [25, 15] which focused in spectroscopy analysis of ancient volcanic rocks as Mars analogues show the effectiveness of spectral analysis for identifying and mapping mineralogical details within rock specimens.

Following the works by [22] and [14], this dataset will be used to train a CNN dedicated to rock classification based on their composition.

Prediction Based Reaction Testing the system on lunar, volcanic, or challenging terrains highlights the rigorous demands placed on robotic systems for autonomous navigation in remote environments. Beyond trajectory planning, ensuring the successful execution of those trajectories is crucial [19]. Reactive methods play a pivotal role in enabling robots to respond effectively to dynamic environmental changes, thus safeguarding the robotic system from harm or catastrophic failure [31]. This paper introduces a multifaceted framework designed to enhance robotic autonomy in various terrains, focusing on tip-over detection, anomalous motion detection, and sensor error compensation. One of the primary objectives of this work is to develop a DL-based model capable of predicting potential tip-over events in real time. By utilizing the Robot Construction Kit (ROCK) framework, the proposed model forecasts the likelihood of a rover tipping over during its mission. This proactive approach empowers the rover to take timely corrective actions, minimizing the risk of accidents [19].

With the help of the terrain classifier and considering the specific terrain conditions, the prediction model is chosen accordingly to suit various terrains, such as sand and rock. The prediction model, powered by deep learning techniques and Long Short-Term Memory (LSTM) modules within an Autoencoder, can handle sequential Inertial Measurement Unit (IMU) data, providing accurate forecasts of tip-over that assist the robot in real-time decision-making. Additionally, the framework addresses anomalous motion detection. By employing the same architecture, it is ensured that the rover can identify unexpected deviations from its planned trajectory, enabling it to make informed decisions to correct its course and avoid potential hazards. To bolster the reliability of robotic systems, a sensor error compensation mechanism is implemented. By leveraging learned prediction models, deviations and failures in sensor values are detected and, if necessary, corrected. This not only enhances the overall system robustness but also enables the controlled recovery of the robot in the event of sensor failures, ensuring safe and effective autonomous navigation.

Autonomous Navigation The Autonomous Navigation uses a Simultaneous Localization And Mapping (SLAM) algorithm using data from the LiDaR, ToF cameras, IMU and wheel positions to generate a map of the environment. The map is then used to plan a path between the rover's current position and a goal position. This plan is then executed while deviations from the plan are handled by simple means like adjusting the heading to move the robot back onto the planned trajectory.

Rimless Rovers Control The rover used in the PerSim project is a hybrid-wheel rover with rimless wheels instead of traditional wheels as seen in Fig. 5. Rimless wheels have been proven to provide better obstacle traversal capabilities [29]. However, the dynamics analysis of such rovers such as the analysis of their possible gaits and gait optimizations remains an open question in research. Single rimless wheels are popularly used within legged robotics research for gait and stability analysis [4, 2, 12]. Within this project, the gait and dynamic analysis from a singular rimless wheel is extended to the entire rover body. Thus, allowing us to reason about the movement tracked by the center of the rover body and even control it for specific goals. One of the motivations is to reduce vibrations of the rover body due to the impact timings of the wheels as this will allow better measurements from the sensors mounted on the rover. For this, the phase portrait of a single wheel of the rover was analyzed (Fig. 7). This phase portrait will be used for the multi-body simulation of the rover with phase-shifts in the wheels to obtain different gaits. The phase-shifts can then be optimized for lowering the frequency and amplitude of the rover movements.

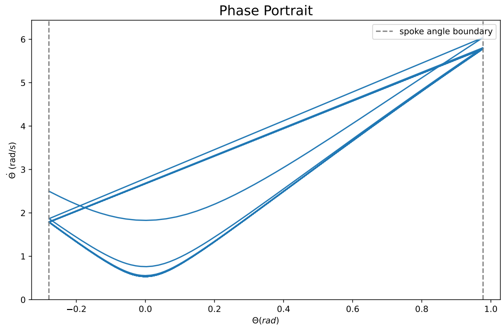

Figure 7: Phase portrait of a single wheel of the rover.

2.2. Long Term Navigation

This subsection describes the variety of adaptation methods for the navigation software that are studied in Persim. Firstly, a repertoire of behaviors is evolved in simulation with the aim of providing the rover the capacity to enact different behaviors towards a same goal. A Gaussian Process is then proposed for direct online adaptation to refine the initial behavior repertoire. Finally, reinforcement learning is envisioned to combine the experiences gathered by the Episodic Memory and the Internal Simulation. Among other factors affecting the selection of one or other behavior, the terrain classification is taken into account.

Behavior Repertoire As first step towards achieving different reliable navigation behaviors an evolutionary process is used to search for a large set of candidate behaviors which perform reasonably well in simulation. The behaviors are defined by Parameter Value Set (PVS) which are set of values to be applied for the parameters of different components the navigation system. The process of evolution consists of the following steps: 1) selection of the parameters and ranges of values in which to search, 2) definition of the missions for training, 3) execution of the evolution process itself, where the different missions are executed, the performance of each PVS computed and the best PVSs selected and stored in the Behavior Performance Map for further generations. [6]

Gaussian Process for Online Adaptation Online adaptation of the parameters of the rover navigation system is done with the Stream Online Gaussian Process Regression (SOGPR) algorithm [8]. The method uses the initial behavior performance map generated by the evolutionary process and keeps evolving the parameters based on the navigation performance that the rover achieves. To gather such performance onboard, traverse evaluation metrics are being developed.

Episodic Memory A topological graph representation has been implemented to store the rover navigation performance information associated with the different locations and time. The graph is composed of nodes representing the different locations and edges representing the traverses that have been attempted to connect them. Along the edges, data products related to the traverse are stored, e.g. the path, as well as performance and context information. The data products can be used again if the traverse is successfully completed, which might lead to a reduction in computational costs. Detailed evaluations are pending to confirm this. If the execution is not successful, the stored information will be used to prevent the same traverse from being executed in the future. The plan is to further use this representation combined with DL techniques to enable long-term generalization capabilities. This way, not only specific locations will be identified as potentially problematic, but also more abstract concepts such as navigation speed for certain trajectories.

Internal Simulation The internal simulation is one of the central components of the long term navigation system. The function of such module is to predict the future state of the rover given state, the environment and an action to be taken. On top of this, a layer of interpretation is needed to identify failures on the simulation. The internal simulation initial development and analysis was performed in projects focusing on the exploration of lava tubes [9, 30] to enhance safety during autonomous navigation.

Both the internal simulation and the episodic memory rely on Envire [3] as a base graph representation for the environment. Envire allows any C++ object to be stored in a location node, which is linked to other nodes by its transformation.

3. SOFTWARE DEVELOPMENT METHODOLOGY

The software development methodology in PerSim is based on agile techniques adapted to the robotics case. The complete project is divided into four iterations, each one including the following stages: feature selection, development, Continuous Integration and Deployment (CI-CD), field testing, and analysis of results. The first two field tests were planned as local campaigns, while the last one took place in a real planetary analog environment located in Vulcano Island, Sicily.

To autonomously and robustly deploy the current software state to the robotic systems, a CI-CD pipeline was established. Using the open-source automation server Jenkins on a build server, daily builds are performed for each workspace. If any errors arise during these builds, they are promptly reported via email to the designated maintainer.

These daily builds are primarily based on Docker images with mounted workspaces and serve two main purposes. First, they are integrated into a GitLab Continuous Integration (CI) pipeline for continuous integration. After each commit, in any of the workspaces repositories, this pipeline triggers an update of the repository and rebuilds it in the corresponding workspace. In case any commit introduces an error, the commit author is notified via email. Secondly, the daily builds are used to initiate the creation of a Continuous Deployment (CD) image after every successful build. Within the CD pipeline, the workspace compiled into a single Docker image with all required dependencies. This image is subsequently utilized to execute predefined automated tests. If these tests pass successfully, the image is appropriately tagged and pushed to a Docker registry. Every robot can then check the Docker registry for updates when starting up, ensuring they always use the latest version of the running workspace.

4. FIELD TESTS

Two field tests have been performed in the project to validate the functionalities on the rover in scenarios similar to a surface on the Moon or Mars.

For the first two field tests, the rover Asguard IV (Fig. 8) was used. The mechanical principles of Asguard IV and Coyote III are very similar, so the results are easily transferable. The availability of multiple rimless wheel rovers allowed the execution of field tests while one of the rover's hardware is been improved.

In order to be able to perform the outdoor tests regardless of the current weather conditions, the Coyote III rover is being made rainproof. To achieve this, a new cover was designed to protect the active cooling from rain. All rotating parts also had to be made rainproof, which includes the connections of the motors to the wheels and the passive rear axles. In addition, some minor updates had to be made for rain-proofing the wiring, the connection of the manipulator to the rover, and the manipulator itself.

4.1. Field Test in Bremen

Terrain Classification Tests These tests were conducted to integrate some of the methods developed within the scope of the Insys project as detailed in [7], which primarily aimed to implement interpretable techniques for NNs applied to planetary exploration. The platform used in these experiments was the Asguard IV robot system.

The first evaluation required that the data from the sensor suite was being successfully collected via the software infrastructure of the rover. This data was then transmitted via the network to a workstation equipped with a GPU, facilitating NN-based terrain classification. This test achieved success, as the data was being received and classified in real-time.

The second evaluation focused on ascertaining the performance of the classifier on unseen data, i.e. on terrains which where not used for training the model. This test encompassed three categories only: rock, sand and concrete types. To ensure robust evaluation, each terrain section needed enough traversable area measuring no less than $2m^2$. Figures 9 provides a visual representation of the setup within a Crater Hall, tailored to replicate lunar analog conditions.

The classifier was trained to categorize six types: rock, sand, gravel, grass, dirt and concrete terrains. However, for the purposes of these experiments, the focus centered on terrains closely resembling planetary landscapes, namely rock, sand, and concrete. Images shown in Figure 9 depict the experimental scenario.

The outcomes of this field test did not yield favorable classification results. Figure 8 presents the prediction summary in matrix form showing how many sample predictions are correct and incorrect per class. The X axis corresponds to the prediction output and the Y axis to the true category. Given the novelty of the test data, it is

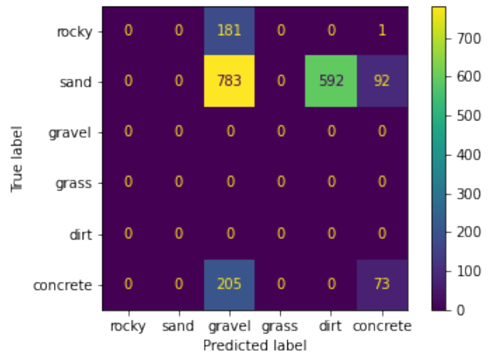

Figure 8: Confusion matrix for terrain classification.

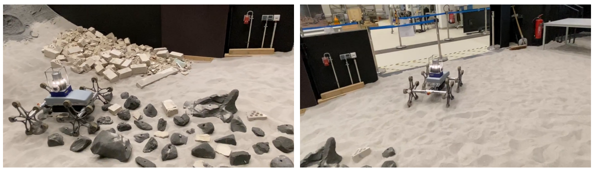

Figure 9: Field test setup for terrain classification.

conclusive that the model does not generalize well to previously unseen terrains. It is noted, however, that the rock class was misclassified as gravel which is quite similar in sensor values from the training data. Furthermore, the sand terrain used for training was more compact than the looser sand encountered in the testing field. It is conceivable that the IMU sensor signature, utilized as input for the NN, shares similarities with the signatures of gravel and dirt recorded in the training logs. Similar issues are noted for the concrete class.

While improving terrain classifiers falls outside of the scope of this project, integrating enhanced models in the future is feasible given the successful execution of integration tests.

Navigation Tests The goal for testing the Navigation Subsystem was to make sure it is working reliably. For this, a suitable start and end position in the testing area was chosen and the robot would have to plan from the start to the end and then execute that plan. Afterwards, the robot would be placed back at the start and the exact same experiment repeated. Figure 10 illustrates a general overview of the motion planner. All of this would then be tried multiple times with different start and end positions.

The robotic rover system Asguard IV was used for these tests. In preparation for the test, a ground truth for the position was deemed useful, so a GPS unit with differential correction was integrated. The position data would not be used for navigation but simply stored for reference. During the Navigation Tests, the GPS receiver was unable receive position data from the satellites despite a clear sky. It was agreed to continue without GPS position data.

During testing, it was found that the initially generated map was too sparse for the path planner to plan from start to end, so the map was first augmented by having the robot drive around the area between start and end using the remote control.

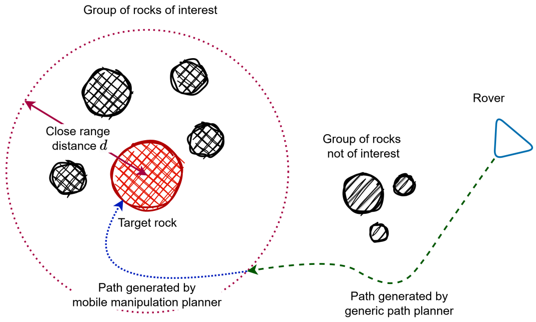

Figure 10: Test of the motion planner switch.

The resulting map quality was often so bad that the path planner refused to start because it either could not find a path or it found the start or end position in an obstacle.

When the path planner created a plan, the path follower would often diverge from the path and then try to rejoin by using a point turn where it should have adjusted the heading slightly. Point turns lead to especially bad odometry, so those occurrences usually ended in an aborted test.

Finally, a few good experiment runs were achieved, but clearly more work was required for the GPS and the other problems resulting in bad map data and path plan execution.

Before the field test in Vulcano Island (see 4.2), more electrical shielding of the rover body was added and improved GPS satellite reception to a point where the position data could be received almost continuously.

After the field test in Vulcano Island, it was found that the orientation from the odometry calculation was reinterpreted as being 180° rotated around the yaw axis. It is believed that this has caused at least some of the problems in map generation and path plan execution. While such a rotation may sound catastrophic, it was not because the map output by the SLAM algorithm is also rotated in the world coordinate system. Errors would only occur when the SLAM algorithm could not compensate for the incorrect rotation from the rover tilting in pitch or roll.

Mobile Manipulation Tests Guidance Navigation and Control (GNC) is responsible of bringing the end effector of the arm close to the region of interest while avoiding any collisions once a particular location has been characterized as a target of interest for close-range data acquisition. The rover will autonomously switch between two motion planners. A basic planner, which considers the rover as a point in space centered at its center of mass to only produce control commands for the joints in charge of the movement of the base. The mobile manipulation planner, which is plans a coordinated motion of the rover and the manipulator arm sending commands to all joints of the system.

The switching of the active motion planner is implemented using Behavior Trees [5]. As long as the distance to the object of interest is larger than a certain threshold, the base motion planner is used. When the close distance is reached, the combined arm-base motion planner becomes active. The motion planner switch was successfully tested during the first field test with Asguard IV.

4.2. Field Test in Vulcano Island

Vulcano is the third largest and southern most island of the Aeolian archipelago. It is also one of the most closely monitored, heavily researched and studied active volcanoes in the world. It hosts the largest unique assemblage of high and low temperature volcanic and hydrothermal minerals. The diverse and extreme environments at Vulcano provide an essential training ground for testing instruments and techniques foreseen for future robotic exploration missions to Mars.

From a planetary perspective, the surface morphology of parts of the Fossa Crater on Vulcano are similar to lunar and martian regions with extremely dry, arid conditions and little or no vegetation cover [20]. Hence, these analog surface conditions at the crater and the environment on the island of Vulcano provide an excellent testing ground for autonomous planetary rovers like Asguard IV.

This year, as in the past campaigns, a variety of spectral instruments ranging from Visible and Near-InfraRed (VNIR) reflectance, Laser Induced Breakdown Spectroscopy (LIBS) to Raman spectroscopy were deployed at various sites for mineralogical, biological, and elemental analysis. The in-situ survey, and its comparison with laboratory standards and instruments, provide an assessment of the usability of these techniques to quickly characterize extra-terrestrial environments.

Environmental Mapping To assess the accuracy of Asguard's environmental mapping capabilities, a suitable area at the base of the volcano was mapped, first with the rover driven manually through the area and then with stereoscopic video footage from a drone used as the ground truth.

Autonomous Navigation In another series of tests, Asguard's autonomous navigation was examined at three different locations on Vulcano. During each test, the rover was given a series of target positions to head for from its current location. Additionally each sequence of traverses was repeated three times, launching from a fixed starting position. All sensor data, navigation goals, execution traces or other available information from the rover were also logged, for later evaluation of the Episodic Memory component still under development at the time.

Two of the aforementioned tests were performed at different locations at the crater of the volcano in a low-vegetation environment with sandy to stony terrain (Fig. 11), and the third trial in a valley with sand, surrounded by rock formations and some vegetation.

While the generation of potential trajectories to the presented targets were generated accurately, execution

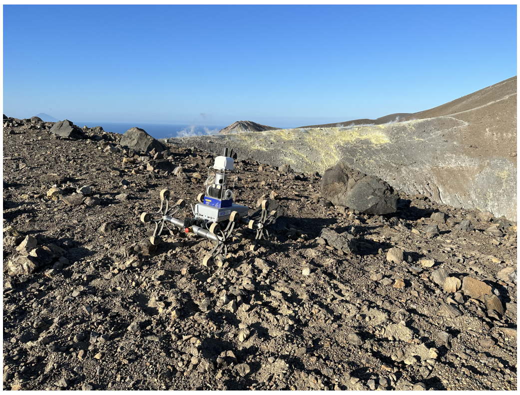

Figure 11: Asguard IV during field tests on the volcano crater at Vulcano Island.

anomalies occurred such as tip-overs. The anomalies likely originated from limited fine-tuning of the navigation parameters resulting in hazardous trajectories. Nonetheless, some promising runs were achieved during the experiments, with the rover successfully reaching multiple targets in succession, autonomously.

5. CONCLUSIONS AND OUTLOOK

This paper presented an overview on the architecture proposed for the development of some of the software modules required for long term navigation and autonomous prospecting of planetary surfaces by a rover.

One of the main challenges of the project involving such a varied set of modules, is the integration and testing. For that purpose an agile approach, tailored to the robotics case, is being used to direct the workflow. The approach involves automatic checks for the software consistency and validity. Validation of the features with rovers in representative locations before the final field test are being performed.

The field test presented in this paper showed that the base GNC, Mobile Manipulation and Terrain Classification work but require improvements. For modules for which results are missing, the plan is to integrate them before the next local field test.

While challenges remain, the project's innovative approaches and methodologies hold great promise for future planetary exploration missions. The field tests conducted as part of the PerSim project have provided valuable insights and set the stage for further refinement and development, ultimately contributing to the success of future robotic missions.

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