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Advancing Operations for Lunar Surface Exploration and Prospecting with Spacefarer: Web-based Operations Software for Space Robotics

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Abstract

The rise of commercial activities on the Moon requires extensible operations tools to support a growing lunar economy. This paper focuses on how rover operations can support increasingly complex science-driven and resource prospecting missions by providing an overview of enabling technologies and operations strategies. First, this paper provides an overview of Mission Control’s participation in the ESA-ESRIC Space Resources Challenge that was focused on technology demonstrations for analogue lunar prospecting mission operations. Second, this paper provides updates on the lunar surface Edge-AI demonstration payload on the ispace mission M1, which will also support science operations of the Emirates Lunar Rover.

Keywords: Lunar rovers, operations software, analogue missions

Acronyms/Abbreviations

Mission Control Software (MCS), Mission Control Academy (MCA), Canadian Space Agency (CSA), European Space Agency (ESA), European Space Resource Innovation Centre (ESRIC), Pan-Tilt-Zoom (PTZ), Laser Induced Breakdown Spectroscopy (LIBS)

1. Introduction

Mission Control is developing Spacefarer, previously known as Mission Control Software, to allow users to remotely monitor and command robotic assets for lunar surface exploration and prospecting campaigns. Spacefarer is a mission operations suite comprised of a microservice architecture and messaging protocol to enable robotic tele-operations in a wide variety of use scenarios. Spacefarer virtualizes the ground segment to enable distributed operations teams to control and supervise remote operations of robotic assets from internet-connected command consoles. This system allows remote users to send telecommands and view telemetry products. Spacefarer can be used as a platform to transmit data between the ground station and users (e.g., operators or the public) or to remotely monitor and control prototype robotic systems in laboratory, analogue, and hardware-in-the-loop testing, with APIs for building custom applications or integrating 3rd party tools, easing the development of advanced user interface technologies for operations.

1.1 Challenges in Commercial Lunar Missions

Between the harsh Lunar environment and economic pressures on companies, early Lunar surface missions will be limited to a Lunar day (14 Earth days). and nominal operations at mid/low latitudes will likely be 10-12 Earth days. Payloads must also share a constrained downlink capacity. Payload operators generating high volumes of data face the problem of not receiving data in a timely fashion to influence their operations or worse, leaving valuable data on the Moon. These constraints are motivating the need for innovative concept of operations and technologies to ensure customer satisfaction, and the viability of this new model of exploration.

1.2 Mobility in Science Operations

Several factors are driving the need for autonomy in mobile science operations. In traditional Mars rover operations, visual surface characterization and subsequent analysis and decision-making takes place in day-long tactical cycles [1]. Upcoming Lunar rover missions, however, will have reduced latency, short lifetimes, and constrained bandwidth. This will result in a need for rapid tactical decision-making processes with limited data, leaving little time to analyze data, identify features of interest, and make decisions.

The highly anticipated NASA VIPER rover that will fly to the south polar region is a large rover (~300kg) but will have a constrained direct-to-Earth communications channel of 230 kbps [2]. Small-scale commercial Lunar rovers will also be constrained; a 10 kg rover deployed in Astrobotic's Mission One will be allocated 200 kbps according to standard payload data rate allocation advertised in their Payload User Guide (PUG) [3]. As per their CubeRover PUG, a 6kg payload will be allocated 60 kbps [4].

Sensing capabilities are growing increasingly powerful, but data transfer rates are not sufficiently high to downlink high volume data in short decision-making timescales. To maximize scientific return, it will be important to have methods to intelligently compress or select data to downlink in real-time or to select key geological features to measure.

The nature of scientific discovery makes onboard autonomy compelling. It increases the chances of detecting valuable novel/sparse features that may otherwise be missed in scenarios that prioritize driving and other mission needs. For example, NASA's Opportunity rover was driven 600 ft past the Block Island meteorite, one of its biggest discoveries, before the science team discovered it and decided to drive back to investigate it [5].

With tactical cycles a few minutes long and pressure to achieve science objectives, missions will benefit from autonomy in data processing and decision-making. The ASAS-CRATERS (Autonomous Soil Assessment System: Contextualizing Rocks, Anomalies and Terrains in Exploratory Robotic Science) system developed by Mission Control offers such capabilities, with the goal of maximizing scientific return in upcoming missions [6].

1.3 State of the Art in Autonomous Perception

In a previous paper [7], we offered a detailed survey of modern perception and modelling technologies for planetary surface robotics. The state-of-the-art in terrain classification leverages high performance Convolutional Neural Networks (CNNs) that find natural features and complex patterns in the image.

For example, Soil Property and Object Classification (SPOC) [8] has a terrain classifier that uses Fully CNNs (FCNNs). Gonzalez and Iagnemma [9] recently published a comparative analysis of CNNs, Deep Neural Networks, and classical algorithms such as Support Vector Machines. These and other works have focused on classifying Mars surface images to improve autonomy for Mars rovers.

For Lunar applications, terrain classification motivated by scientific research has focused on crater detection using orbital data. Stepinski et al. and Chung et al. offer a review of traditional machine learning techniques, including SVMs [10], [11]. More recently, Silburt et al. [12] explored the use of CNNs to detect craters using a DEM merged from LRO and Kaguya data.

While these studies have successfully demonstrated the use of deep learning to improve terrain classification of images from Mars rover datasets or from a laboratory setting, only recent work by Mission Control has holistically studied terrain classification in a real-time system for a science-driven rover mission and its implications on mission operations [13]. Additional work, as presented in this paper, has demonstrated the use of this technology on Lunar datasets.

The Mission Control terrain classifier was first developed under the CSA-funded Autonomous Soil Assessment System [14]. In 2019, it was used onboard a rover to classify eight Mars-relevant terrain types in real-time at ~15 FPS as the rover drove at 20cm/s at a high-fidelity analogue site in Iceland (see Fig 1). This was a part of SAND-E (Semi-Autonomous Navigation for Detrital Environments), a NASA PSTAR funded project to inform Mars2020 operations [13].

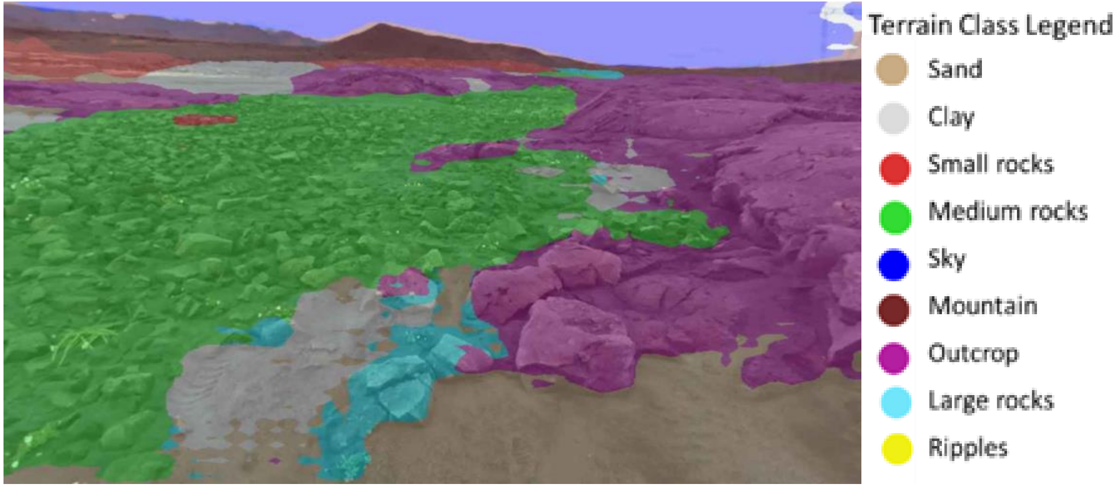

Fig 1. Result of our AI-based terrain classifier deployed for a Mars2020 operations study in Iceland.

1.4. Lunar Surface Exploration and Prospecting Use Cases

Spacefarer has been developed and tested in dozens of analogue rover missions led by Mission Control for advancing mission operations with Spacefarer to support Lunar surface exploration and prospecting use cases. This system has been sold commercially and used in hundreds of hours of remote robotic mission operations since 2016, including for CSA and NASA-funded Lunar and Mars analogue missions.

The development of Spacefarer is advanced through continuous analogue operations campaigns in Mission Control’s indoor lunar analogue terrain facility at its Ottawa location, shown in Fig 1, which allows direct user feedback into the software development workflow. The terrain facility includes several topographic features representative of the lunar surface, and the lighting can be adjusted to represent various lunar surface lighting conditions. Lunar analogue rocks and simulants are added to the environment dependent upon the analogue operations scenarios.

Fig. 2. Mission Control’s indoor reconfigurable lunar analogue terrain

Spacefarer allows remote users to teleoperate a rover platform in the analogue terrain. The rover can be controlled via gamepad, distance and heading commands, and waypoint path-planning (example in Fig 3). The camera images can be streamed for live operational scenarios and sent back as stills to simulate the concept of operations for lunar missions. Additional cameras and instruments, such as a pan-tilt-zoom (PTZ) camera, allows the user to switch views for navigation or science investigations. Spacefarer also incorporates a point-cloud viewer for visualizing lidar data.

Fig. 3. Waypoint path-planning in the user interface

Deploying the remote and distributed operations capability of Spacefarer in the analogue terrain facility permits frequent operations testing and training in support of software and operations development. This strategy has been leveraged to support two use cases for Spacefarer: The Space Resources Challenge and the Emirates Lunar Mission (ELM).

2. ESA ESRIC Space Resource Challenge

Mission Control was selected among 13 teams to participate in the European Space Agency – European Space Resource Innovation Centre (ESA – ESRIC) led Space Resources Challenge in November 2021 in the Netherlands and was then selected among the top 5 teams to participate in the second round of the Challenge in Luxembourg in September 2022. The goal of this challenge was to demonstrate technologies for lunar prospecting using a rover platform. The challenge included both navigational and scientific criteria to be met within limited timeframe.

For the first round of the challenge, the operation and targeting of a pan-tilt-zoom (PTZ) camera was integrated into Spacefarer. The science objective for the challenge was to identify and characterize the composition of six rocks in the indoor landscape. The layout and specifics of the challenge were purposefully unknown prior to the start of the timed challenge. The team successfully identified and visually characterized all six rocks, and the overall operations were completed successfully and efficiently. The team's efficient operations during the live challenge were largely thanks to multiple training sessions and an iterative software design approach, using the rover in Mission Control's analogue terrain facility.

The second phase of the Challenge required a 2500 m^2 region of interest (ROI) to be explored, mapped, and prospected for resource potential within 4 hours. The ROI was set up as a south lunar pole analogue with challenging lighting conditions, and various features of interest to investigate. A 2.5-second latency in each direction and random communications drop-outs were incorporated to emulate a lunar mission scenario, allowing judges to evaluate the approaches taken by teams to handle the communications challenges.

As a software-focused company, Mission Control entered the Space Resources Challenge with a solution based on the following elements:

- Focus on operations software technology and strategies based on our Spacefarer platform.
- Rigorous practice and operational readiness by the team, leveraging our easily accessible indoor lunar analogue testbed
- Leveraging reliable COTS hardware components, such as the Clearpath Robotics Husky, NVIDIA Xavier developer platform, the PTZ camera, and Zed-2 stereo camera.

Mission Control also incorporated instruments from key partners:

- The mWABS, a compact, next generation, 2-axis scanning LiDAR, from Canadian space robotics and sensing company MDA, and

- The L3VIN LIBS (Laser Induced Breakdown Spectroscopy) from US-based Impossible Sensing.

The Mission Control team remotely operated their rover system in the ROI with Spacefarer, which was tolerant to the latency and random communications dropouts. The team relied upon the visual overlays, including the distance, wheel tracks, and PTZ field of field overlays, as shown in Fig 4, for safely navigating the ROI. Within the ROI were several features such as boulders, mounds, and craters. Fig 5 shows a boulder resting in a crater in both a camera view and lidar point cloud view.

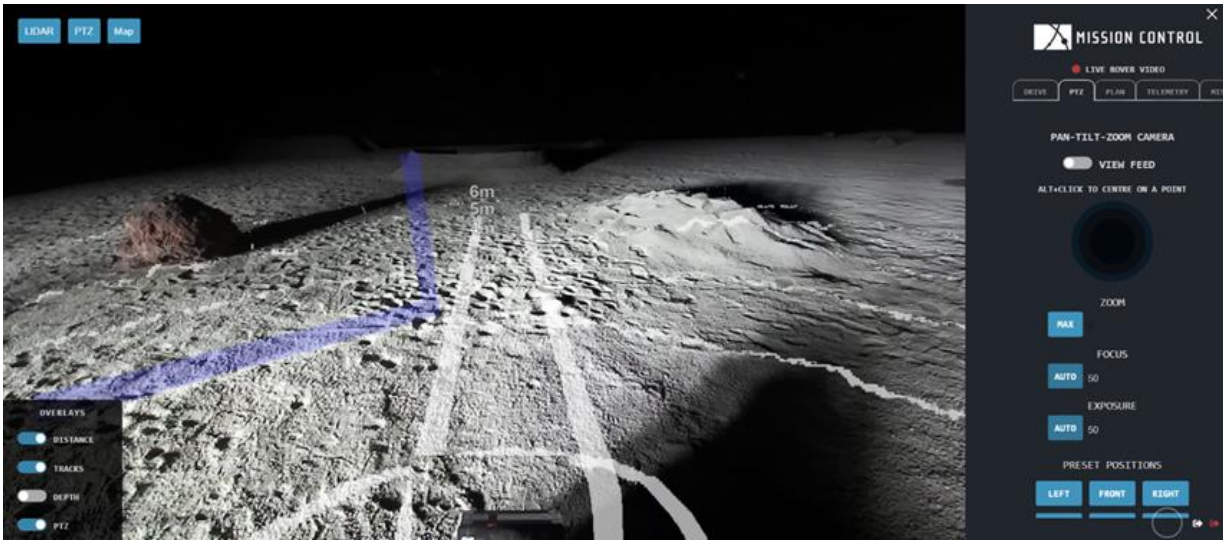

Fig. 4. Spacefarer's user interface showing with overlays enabled to support safe rover navigation over the communications latency.

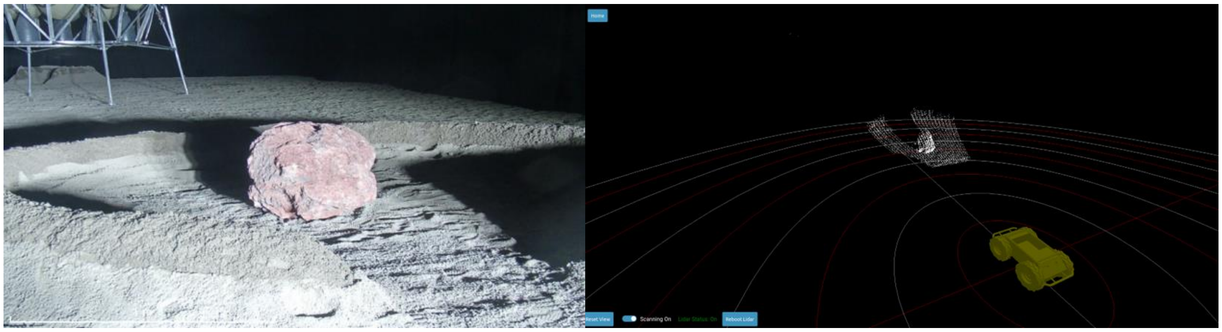

Fig. 5. A boulder shown in the camera viewer (left) and in the lidar point cloud viewer (right)

These features represented the science targets for investigating and adding to a prospecting map. The strategy for science investigation with Spacefarer was to capture context imagery with the stereo camera to identify features for investigation, using the PTZ camera to get close-up imagery, and then positioning to acquire LIBS data if the target was deemed visually to be of interest. An example of a captured LIBS spectra of an aluminum sample is shown in Fig 6.

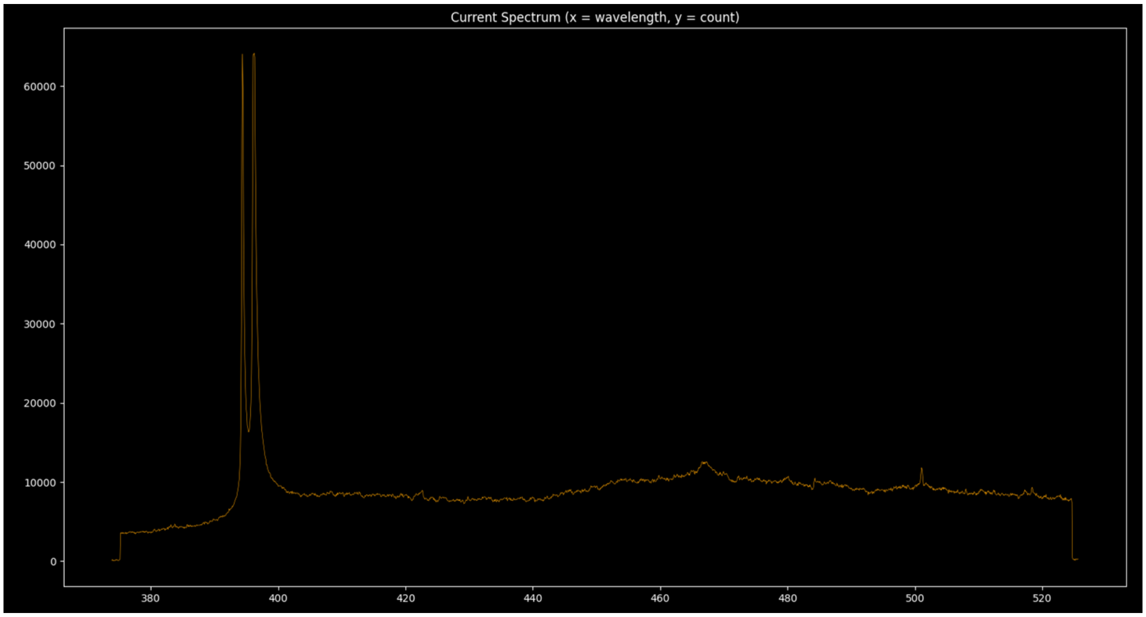

Fig. 6. Example of aluminium spectra in the LIBS data viewer

The Challenge required teams to output a DEM and labelled prospecting map. A SLAM mapping tool integrated with Spacefarer produced a 3D representation of the explored area, with an example shown in Fig 7. Capturing images with the PTZ camera and the LIBS automatically appended a label to the map, with an example shown in Fig 8.

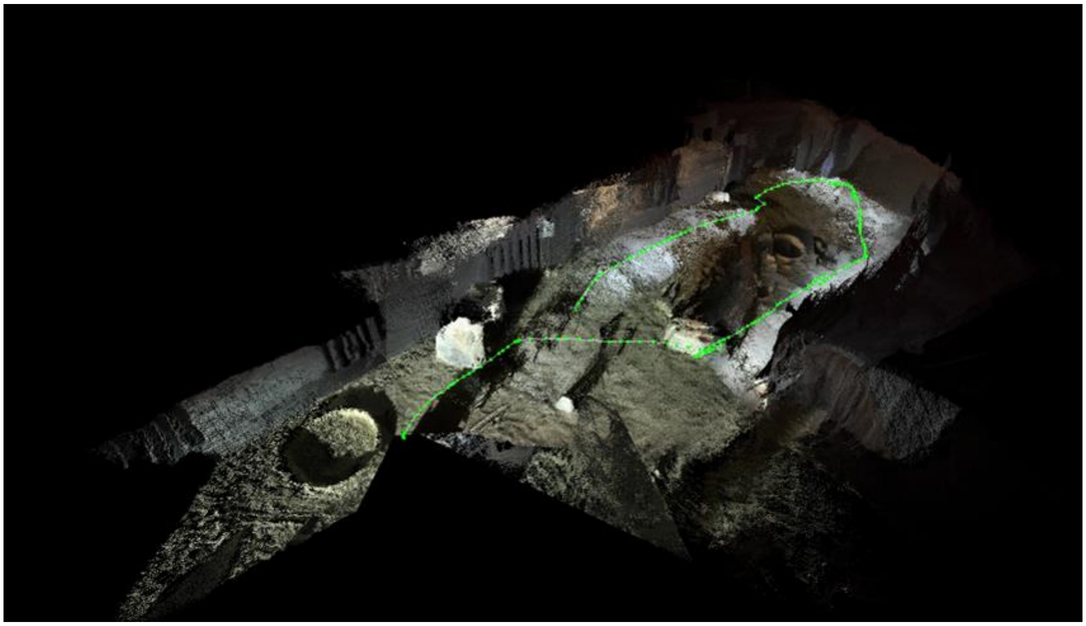

Fig. 7. Sample of the 3D map generated in Mission Control's Moonyard showing the path the rover traversed.

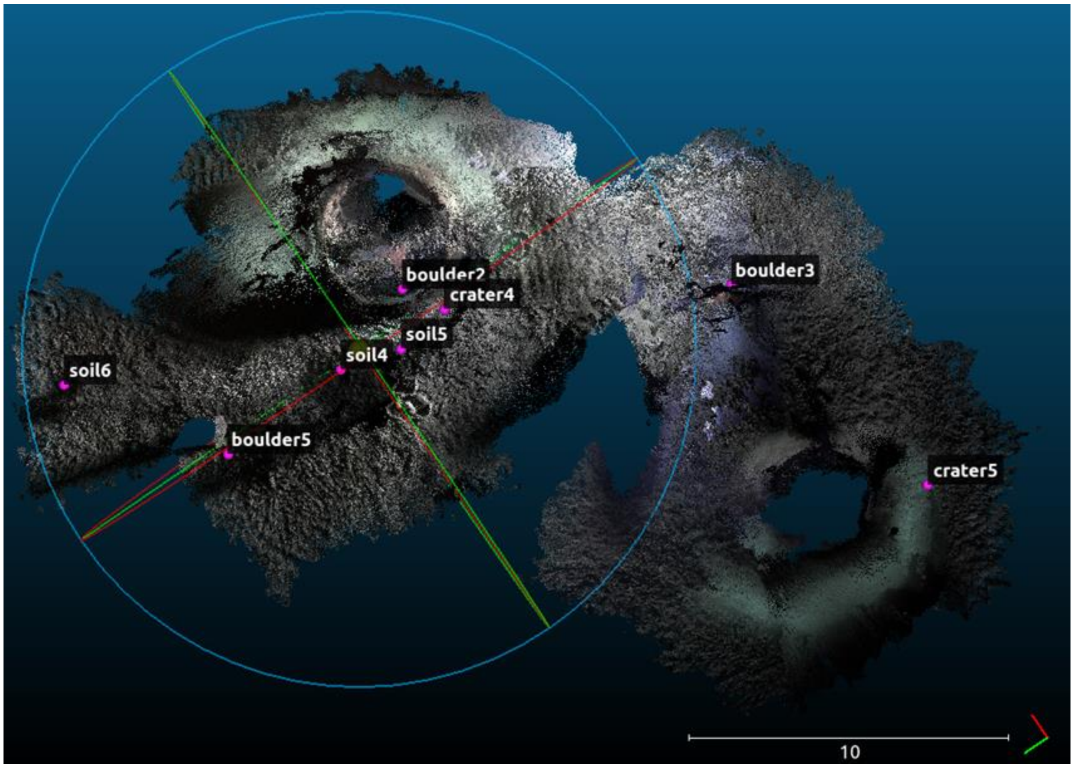

Fig. 8. Sample of the 3D map generated during the Space Resources Challenge with the labelled locations from where science measurements were captured.

3. Emirates Lunar Mission Science Team Support

Mission Control is also advancing Spacefarer to support their science team in its research investigations as participates in the international science team of the Emirates Lunar Mission.

During the mission duration, Mission Control will operate MoonNet, a Deep Learning based terrain classification model, deployed onboard the ispace lunar lander, which will process images from the ELM *Rashid* rover's primary navigation camera, classifying each pixel based on a scheme defined by our science team. This is anticipated to be the first demonstration of Deep Learning on the lunar surface.

In the ground segment, Spacefarer will incorporate a version of MoonNet, an example of which is shown in Fig 9, that will allow science team members to visually overlay data products on top of the primary navigation camera view. Additional overlays include projected rover tracks and radial distances. Spacefarer also allow science team members to suggest paths for rover traverses.

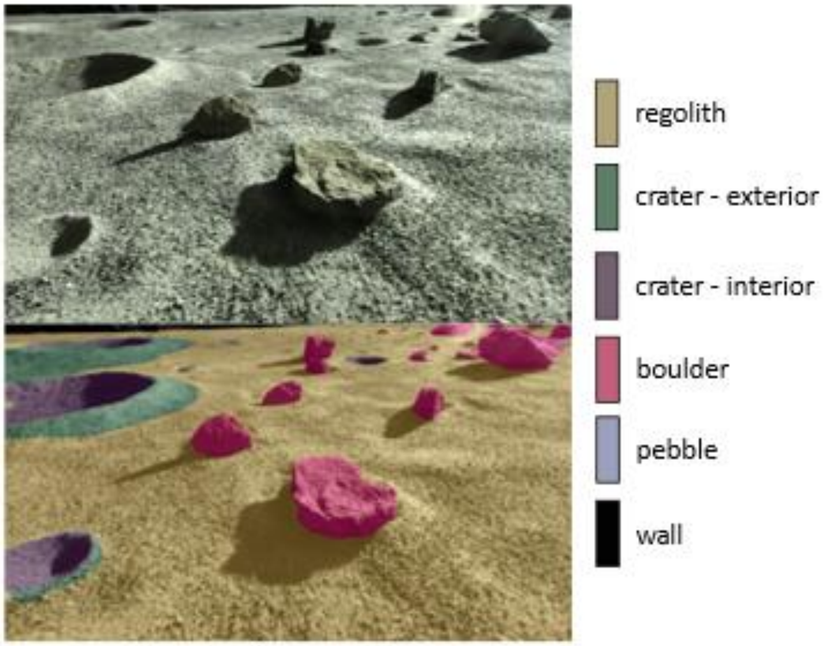

Fig. 9. Example of output from Mission Control's AI-based MoonNet that will be demonstrated as part of the ispace M1 mission.

Spacefarer will be deployed in the analogue terrain facility to support the development of science operations procedures prior to mission operations and mission operations rehearsals. This development of science operations helps to inform the science team members how to streamline their procedures for improving efficiency during the mission.

4. Education and Public Outreach

Mission Control leverages Spacefarer to support education and public outreach campaigns in conjunction with its operations campaigns. Spacefarer has powered educational missions deployed under Mission Control Academy, an immersive technology-based education and outreach program. MCA challenges participants to design and operate a planetary exploration mission, culminating in an opportunity to remotely drive a real rover in a lunar-like environment. To date, Mission Control has delivered MCA to hundreds of students in four continents, with an example of MCA shown in Fig 10.

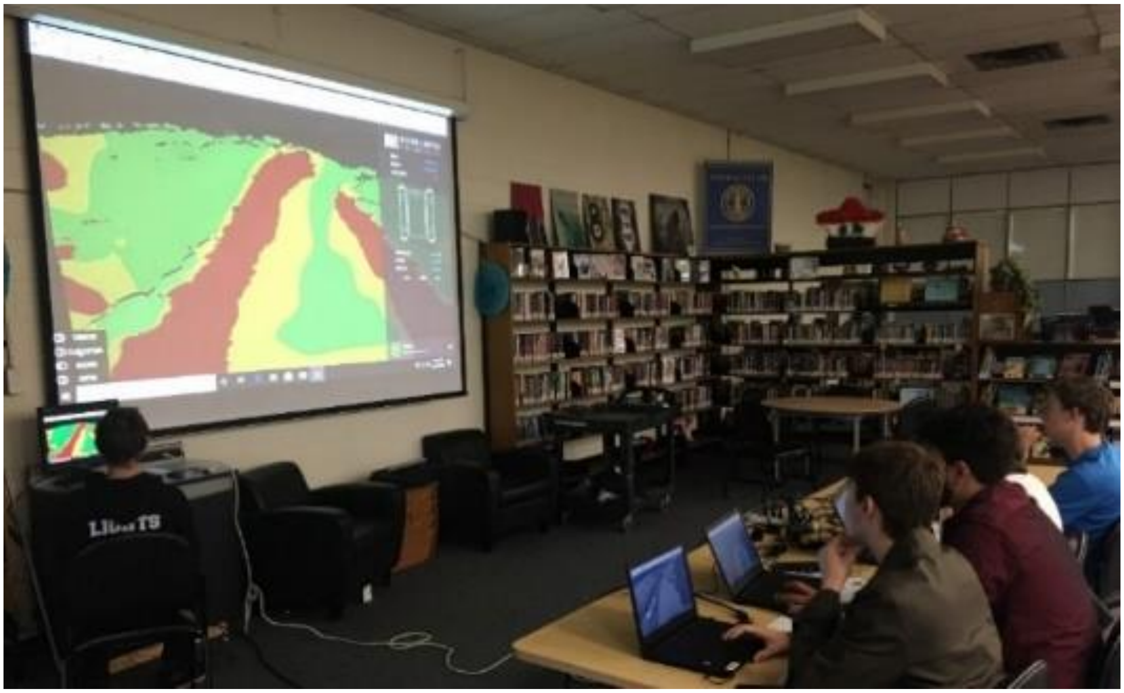

Fig. 10. Woodroffe High school students in Ottawa participating in Mission Control Academy missions.

The mission scenario asks participants to assume realistic roles in a mission to the Moon or Mars. Working together on a high-stakes space mission highlights important interdisciplinary communication and teamwork skills in an incomparable learning environment. Furthermore, teams will have the opportunity to learn from professionals in the space industry who have worked on robotic space missions.

5. Conclusions

Mission Control has developed a modern suite of flight software applications and operations software tools that teams can use for their surface missions to maximize their mission efficiency. The demonstration and TRL advancements of these capabilities in upcoming flight and analogue demonstrations will pave the way for future AI-enhanced robotic missions.

Acknowledgements

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