Automated Characterization of Planetary Surface Geological Features from Surface Spacecraft Cameras to Support Mission Operations. K. V. Raimalwala[1], M. Faragalli[1], M. M. Battler[1], E. P. Smal[1], M. Cole[1], M. Cross[1], and J. E. Reid[1], [1]Mission Control Space Services Inc., kaizad@missioncontrolspaceservices.com, 162 Elm St. West, Ottawa, ON K1R 6N5, Canada

Introduction: The characterization of a planetary surface from visual imagery is a common initial step in almost every scientific investigation that may then use specialized instruments for remote sensing, contact sensing, and sample analysis. Understanding the formation and evolution of a geologic setting requires an understanding of what facies are present in the scene, their layout, geometry, density, and the contact boundaries and spatial relationships between them [1].

Autonomous characterization of a planetary surface using standard colour imagery can enable autonomous decision-making onboard or support analysis in the ground segment, beneficial for most planetary science missions that face communications and computational constraints. The ASAS-CRATERS (Autonomous Soil Assessment System: Contextualizing Rocks, Anomalies and Terrains in Exploratory Robotic Science) suite of science autonomy applications developed by Mission Control offers such capabilities to help maximize scientific return in upcoming missions [2]. It comprises deep learning algorithms for terrain classification and novelty detection using convolutional neural networks (CNN), and for data aggregation to produce relevant data products for supporting science operations. Built on cutting-edge algorithms and off-the-shelf flight processors, it offers low-cost ways to speed up analysis of planetary surface imagery and tactical decision-making in next-generation lunar and planetary missions.

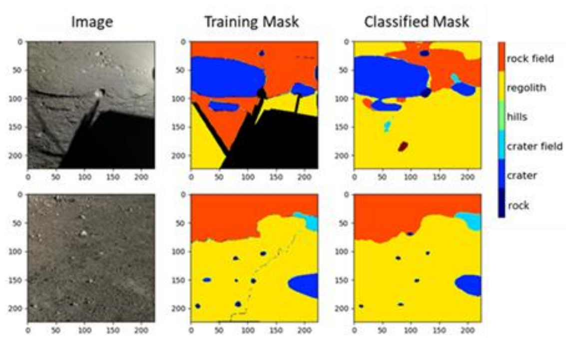

Figure 1: *Two examples of deep learning based terrain classification using Chang'E-3 Yutu-1 images.*

Motivation and Use Cases:

Onboard Autonomy for Science Instruments. There are several motivating factors that drive the need for autonomy in science operations. In traditional Mars rover operations, visual surface characterization and subsequent analysis and decision-making takes place in day-long tactical cycles [3]. In lunar rover missions however, reduced latency coupled with shorter mission durations will require very rapid tactical decision-making processes. This means less time to analyze data, identify sites to explore, and conduct trade-offs regarding navigation. In other deep space surface missions, we can expect communication bottlenecks, making automated surface analysis important for automated instrument targeting or downlink decisions.

Any AI-based decision-making process onboard will require a semantic representation of the terrain. Once an onboard system can infer some knowledge of the surrounding terrain's geological features, it can also be programmed with some decision-making capabilities. Inspired from methods used in Mars rover missions [4], we plan to investigate methods to use outputs of the terrain classifier and novelty detector to inform intelligent prioritization for data downlink or instrument targeting: 1) novel features, 2) representative sampling to capture pre-specified distribution of known features, and 3) high-priority classes such as a fresh crater.

The first use of this technology for a science instrument is the I-SPI (Intelligent Sensing and Perception in Infrared) thermal imager instrument that is currently in Phase 0 development with funding from the Canadian Space Agency [5]. I-SPI is targeted for a lunar micro-rover mission, and this technology will provide onboard support for autonomous targeting and downlink prioritization decisions.

Supporting Ground Segment Operations. ASAS-CRATERS can support mission scientists and instrument operators in several ways. If a particular geological feature is classified and extracted to create a digital object, it can be further processed, distributed, archived, and used in many ways across the mission operations team. In low-latency architectures for lunar or NEO missions where near-real-time decision-making is possible, this autonomously annotated object can be efficiently evaluated by a science team and selected for further analysis. This can be particularly useful for rover missions where scientists may sometimes only have a few minutes to make decisions in between rover stops.

For geological features classified from stereo imagery (or if other correlated depth information is available), they can be projected onto a map frame and aggregated from multiple images to build a rich map-based data product that can more easily be integrated into GIS tools for rapid analysis with the context of scale and other information layers derived from *in situ* or orbital sensors.

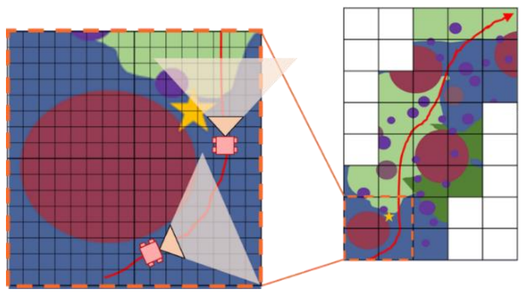

Figure 2: *An illustration of aggregating outputs from the terrain classifier onto map tiles.*

In all cases, features can be catalogued in a database, enabling feature-based query in real-time, e.g., an operator can quickly retrieve all fresh craters of size 3-4m in a specific geographic area. This can make analysis and decision-making more efficient, especially for short-duration cycles or for long-range rover missions that cover large areas. The rapid classification and cataloguing of lunar surface features supports analyses, e.g. crater counting and size-frequency distribution estimation. This can help scientists to inform their models and hypotheses that might guide decisions within a short mission.

Results and Future Work: The terrain classifier was first developed under the Autonomous Soil Assessment System project by Mission Control, funded by the Canadian Space Agency (CSA) [6]. In 2019, it was used to classify eight Mars-relevant terrain types in real-time at ~15 FPS from images taken by a rover driving at 20cm/s. This was a part of SAND-E (Semi-Autonomous Navigation for Detrital Environments), a NASA PSTAR funded project led by Dr. Ryan Ewing at Texas A&M University, which integrates robotic terrain analysis and drone mapping to study operations strategies in Iceland in support of the Mars 2020 mission.

Figure 3: *Classifier output overlaid on one camera image during a SAND-E traverse in Iceland field tests.*

A second field season for SAND-E is planned in the summer of 2021, where additional experiments will be done to synthesize statistical summaries of the geological features classified over the duration of a rover traverse, in support of science team operations.

Since 2019, the terrain classifier is undergoing development for lunar surface exploration applications. Preliminary prototyping was completed using datasets from Chang'E 3 and 4 missions as well as a high-volume dataset, generated specifically for training the CNN, from a lunar analogue testbed at Mission Control HQ in Ottawa, Canada. A sample of this dataset may be published for public use in 2021.

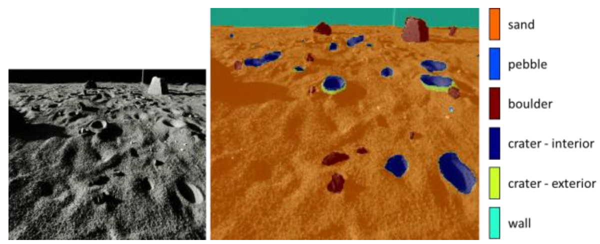

Figure 4: *Recent demonstration of classifying macro-level geological features in one image of the Mission Control lunar analogue testbed.*

The terrain classifier is currently at TRL 5 and is undergoing prototyping on a flight-qualified embedded processor by Xiphos Systems. A flight demonstration is targeted for a lunar mission in 2024, and research investigations will study the use of some of the operations support strategies highlighted in this abstract. Refer to Raimalwala et al. [7] for more technical details and testing results of the terrain classifier.

Acknowledgments: The authors thank the CSA for funding this technology, and the ASAS-CRATERS partners for science and technology support: Dr. Krzysztof Skonieczny at Concordia University, Dr. Ed Cloutis at the University of Winnipeg, Dr. Gordon Osinski and Dr. Kenneth McIsaac at Western University, Dr. Ryan Ewing at Texas A&M University, and Xiphos Systems Corporation.

References:

[1] Francis R. et al. (2014) *SpaceOps*. DOI: 10.2514/6.2014-1798. [2] Raimalwala, K. et al. (2020) Lunar Surface Science Workshop, LPICo 2241, p5124. [3] Gaines D. et al. (2016) *PlanRob*, 115-125. [4] Castano R. et al. (2007) *JFR*, 24, no. 5, pp. 379–397. [5] Battler M. M. et al. (2021) *LPSC* no. 2548 [6] Faragalli M. et al. (2018) *i-SAIRAS*. [7] Raimalwala K. et al. (2020) *i-SAIRAS*.