FIELD DEMONSTRATION OF GAUSSIAN PROCESS ACTIVE LEARNING OF ROVER MAPPING SPECTRAL COMPOSITION IN HAWAII'S LUNAR SURFACE ANALOG. S. Akins[1], J. Nakano[1], R. Matsumoto[1], H. Wang[1], F. Zhu[1] [1]University of Hawaii (1680 East-West Rd. POST 524B, Honolulu HI 96822 and [sakins], [jmnakano] , [riverjm], [wanghao], [zhuf] @hawaii.edu) .

Introduction: This paper investigates the performance of a rover equipped with an ASD FieldSpec 4 Spectrometer tasked to map the spectral composition of an analog planetary environment on Mauna Kea, Hawai'i. The rover's onboard computer runs a Gaussian Process active learning algorithm, with the intention to comprehensively map the environment while reducing reliance on human intervention — a critical advantage for operations in space that limit communications and emphasize ambitious mission timelines. Key performance metrics, including model accuracy, convergence, and samples collected, are evaluated to assess the algorithm's effectiveness in intelligent exploration. Mechanically, the rover provides mobility to a location, calibrates the spectrometer with automated white referencing, and measures payload readings with an active light source shielded by an awning. This research demonstrates the rover's adaptability and reliability in analog extraterrestrial environments, moving us closer to a rover with increased autonomy suitable for space operations.

Background: The University of Hawai'i at Manoa's Robotic Space Exploration (RoSE) Laboratory has previously mapped spectral-spatial distribution of terrain material and conducted simulations of rover movement and decision making powered by a Gaussian Process active learning model.

Spectral-Spatial Investigations on Hawai'i [1]: Mauna Kea, a dormant volcano located on the Big Island of Hawaii, is a test site that research agencies around the world leverage to rehearse space operations. One such program was the 2010 International Lunar Surface Operations In Situ Resource Utilization Analog Test, which was a coordinated effort amongst the Canadian Space Agency, the German Aerospace Center, and the National Aeronautics and Space Administration, with the assistance of the PISCES program hosted through the University of Hawai'i at Hilo [3]. Researchers with RoSE Lab gathered measurements that provided insight into the locations across Mauna Kea which have the highest correlation with the lunar surface samples collected from the Apollo 11, 12, 14, 16, and 17 missions. According to the spectral-spatial investigation, multiple spots on Mauna Kea have high spectral similarity to the samples collected from the highlands of the Moon. One of these spots, detailed in the methodology section, was utilized as the testing site for rover data collection.

Active Learning for Constrained Trajectory Exploration [2]: Active learning has the potential to dramatically decrease mission timelines for exploration missions by increasing autonomy of robots. Mobile robots, like rovers, traverse environments in trajectories constrained to the surface environments along a sequence of waypoints. Historically, these waypoints are dictated by human teleoperators but waiting on this communication elongates the mission timeline and increases risk of failure. Naive autonomous exploration preloads an exploration pattern to ensure gridded coverage of the environment but these science-blind methods are inefficient. Active learning incorporates historical measurements to train a surrogate model (Gaussian Process) that predicts the spatial distribution of a target variable of interest. Previous results show that active learning strategies are more sample and distance efficient in proposing information dense trajectories while also offering model convergence.

Hardware Implementation: The current rover design is contained in a 4U (borrowed from cubesat convention) rover structure, complete with an ASD FieldSpec 4 Spectrometer as seen in Figure 1.

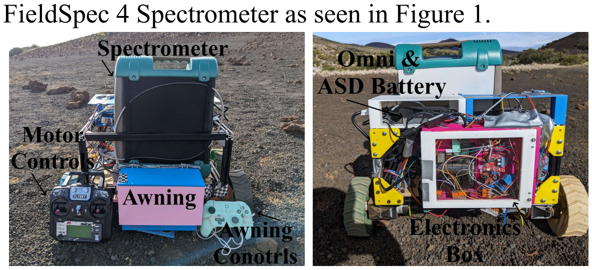

Figure 1: Rover attached with all hardware on lunar surface analog

Several measures are taken to ensure data collection can produce consistent results without being restricted by natural lighting conditions. The rover awning ensures the fiber optic cable terminal is shaded from external light sources. An artificial light source is utilized to ensure that the lighting conditions at every site are consistent. Along with this, the spectrometer's white referencing mechanism, which calibrates the spectrometer, has been automated. The electronics utilized on the rover consist of a Jetson Orin Nano Devkit, two Roboclaw motor controllers, one relay attached to two LED lights, a U-blox ZED-F9R GPS, an ANNIMOS digital servo, and an L298N motor controller for the rover's linear actuator. The batteries utilized are 71Wh "Omni 20+" portable power banks fitted with AC, DC, USB-A, and USB-C charging ports. Two are onboard the rover for normal operations, along with the ASD 4 spectrometer battery.

Methodology: A field demonstration was conducted March 18th - 22nd, 2024. This test utilized correlation data from the first spectra sampled on the grid when taking ground truth measurements.

Active Learning Algorithm: The Gaussian Process Active Learning (GPAL) algorithm, fitted with a Matern kernel, is outlined in Algorithm 1.

Algorithm 1 Gaussian Process Active Learning

1: Select n random samples from D_{sample}
2: Add n samples to D_{train}
3: **for** i = 1 **to** $D_{sample}/2$
4: Train Gaussian Process model with D_{train}
5: Calculate Uncertainty = CB_{upper} - CB_{lower}
6: Identify nearest neighbor with the highest uncertainty
7: Move to location of highest uncertainty and append measurement to D_{train}

Experimental Design. The experimental plan was based heavily around battery capacity and weather conditions. The trajectory suggestion policy (the contribution of this work) is autonomous while other operations, such as movement and payload operations, are manual. Testing began with gathering ground truth data, followed by utilizing the active learning model. The grid size for the testing site was an 11x11 square (121 testing points), with each point being 2m apart (484m^2 area). A science-blind trial was run in a snake pattern prior to performing the first active learning trials. This data was utilized as the ground truth. In total, two ground truth and six active learning trials were taken. GPS coordinates of the [0, 0] grid point are as follows: N 19°45.4791 W 155°27.5006.

Preliminary Results: Figures 2 and 3 depict the trajectory of the rover on the surface. Figure 4 shows the variance and RMSE of the samples. The active learning trial converges in 54 samples as compared to 102 for the science blind method. RMSE for the AL method is higher than in the science blind, however, weather conditions and exact sample location are not consistent. If we were to sample the ground truth spectra along the active learning path, GPAL would converge to the minimum RMSE.

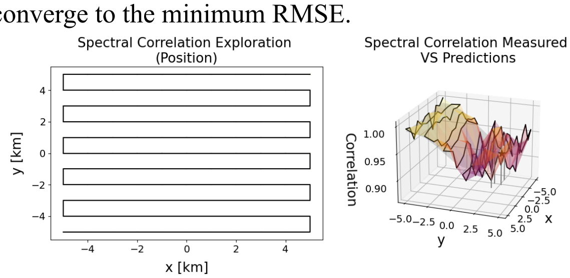

Figure 2: Science-Blind Active Learning Method

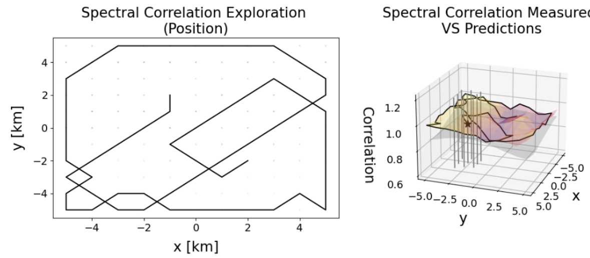

Figure 3: GPAL Algorithm

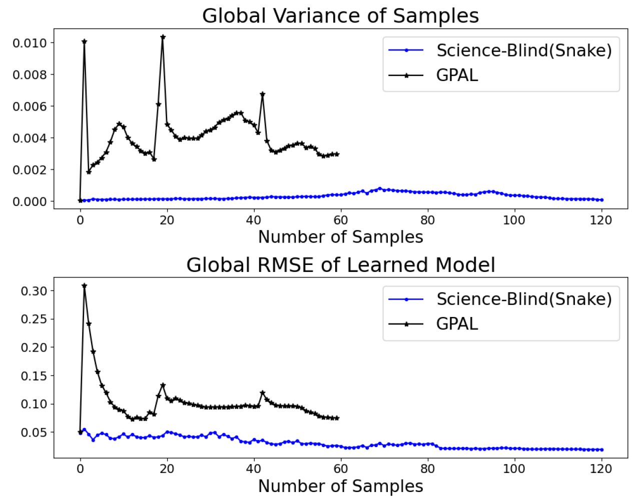

Figure 4: Variance and RMSE of Science Blind VS AL Method

Conclusion: Integrating a GP active learning algorithm on a rover and testing its performance on a planetary analog is a large step forward in developing rover autonomy for future space exploration. Through this research, we provide insight to the enhanced performance of autonomous active learning in a real environment that is traceable to space missions, which won't require human teleoperation.

References:

[1] Wang H. et al. (2023) *Aerospace Research Central,* 1-24.

[2] Akins S. and Zhu F. (2023) *Aerospace Research Central,* 1-15.

[3] Kate I. L. et al. (2013) *Journal of Aerospace Engineering,* 1-14.

Acknowledgements: This work was supported by NASA Grant HI-80NSSC21M0334 and Catalyst Awards for Science Advancement Grant NASA SSERVI #80NSSC20M0027. The accommodations for our field trips were supported by Hale Pohaku and PISCES staff. We'd also like to thank Hawaii's Department of Land and Natural Resources (DLNR) for securing our field testing permit.