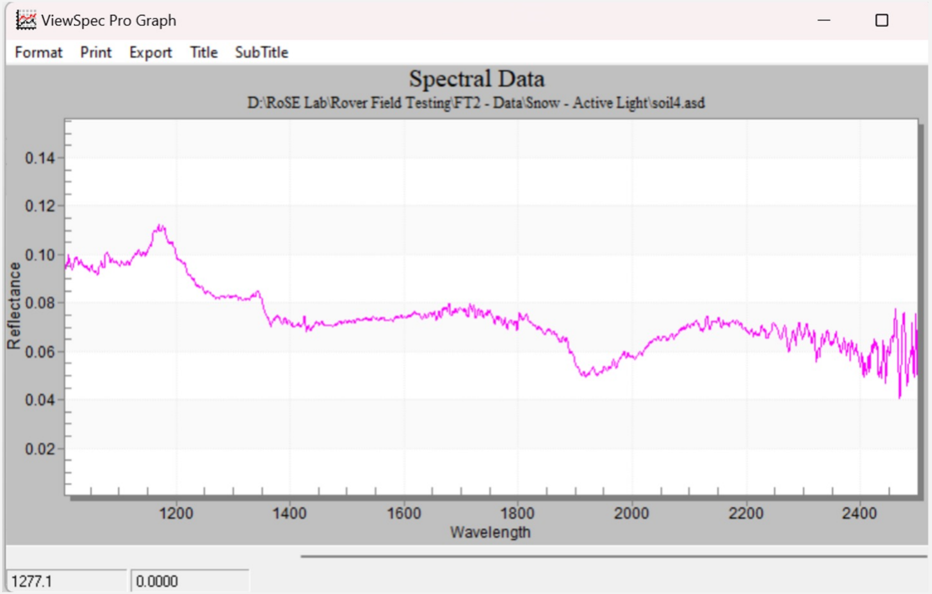
Field Demonstration of Gaussian Process Active Learning of Rover Mapping Spectral Composition in Hawaii's Lunar Surface Analog



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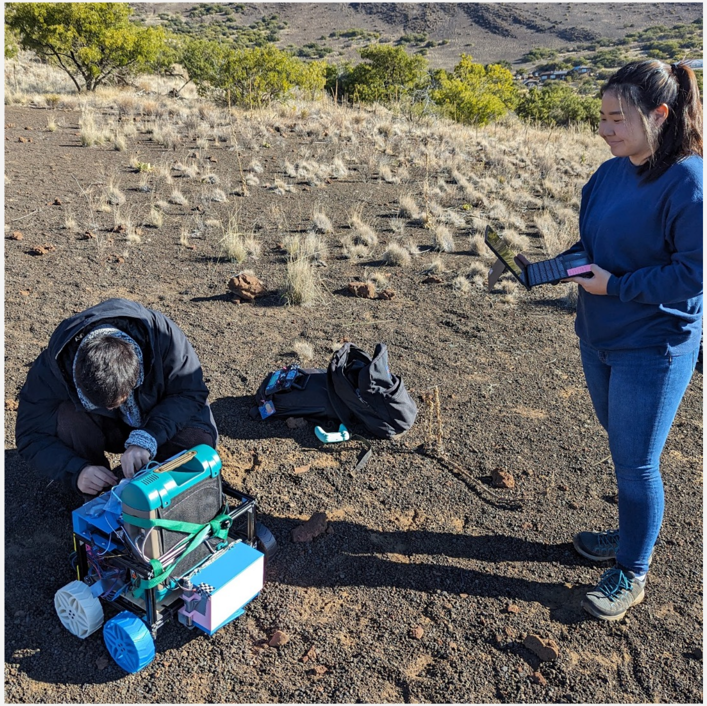
University of Hawai'i at Mānoa

Overview

- Introduction & Motivation
- Background
  - Spectra-Spatial Characterization
  - GP Active Learning
  - Hardware & Avionics
- Methodology
  - Experimental Campaign
  - Machine Learning Implementation
- Preliminary Results
- Conclusion & Future Work



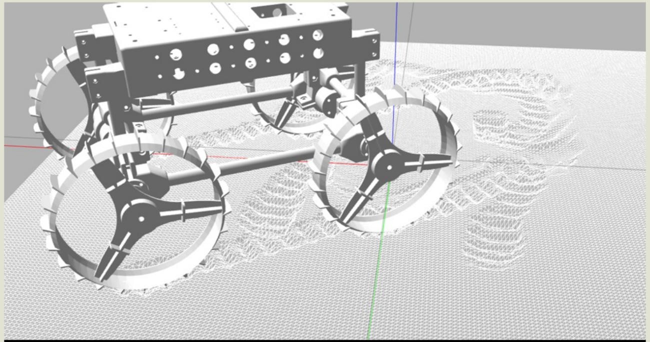
Introduction & Motivation

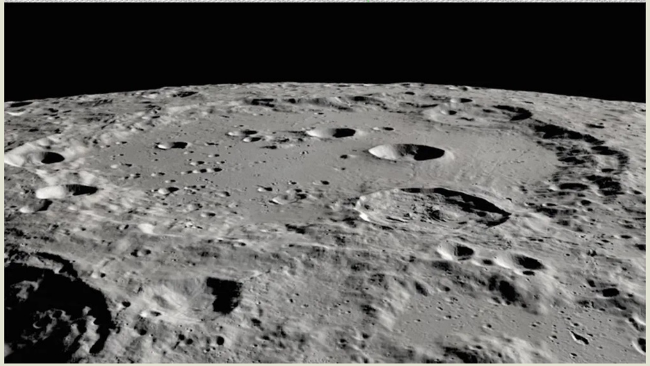
Research Goal:

Autonomous planetary surface exploration

Analogue Field Test Objectives:

1. Investigate the analogue through spectral measurements.
2. Characterize water ice spectrum across a lunar surface analogue.
3. Demonstrate an active learning algorithm in a lunar surface analogue.





Utilize a spectrometer on a rover with machine learning to collect spectral data from the soil

[trajectory suggestion policy = autonomous & movement/payload operations = manual]

Overview

Research Goal:

Autonomous planetary surface exploration

Previous Research:

1. Investigate Mauna Kea spectrally
2. Investigate performance differences between ML algorithms

Application:

Gather sectral data spatially distributed in real environments *autonomously*

Past

Determine locations on Mauna Kea with highest correlation to the lunar surface

Determine an effective ML algorithm to utilize for mapping water-ice distribution on a lunar surface

Current

Construct a rover that collects spectral data in a lunar analog, generating an model of the surface

Future

Have the rover autonomously map the distribution of water/hydroxyl in its environment

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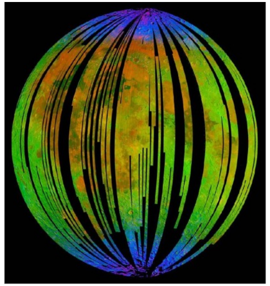
Chandrayaan-1



Determine locations on Mauna Kea with highest correlation to the lunar surface

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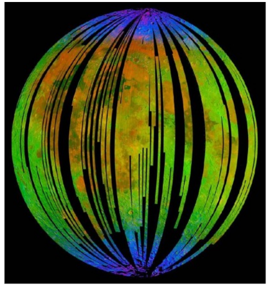


Determine locations on Mauna Kea with highest correlation to the lunar surface

↓

Determine an effective ML algorithm to utilize for mapping water-ice distribution on a lunar surface

↓

Current — Construct a rover that collects spectral data in a lunar analog, generating an model of the surface

↓

Future — Have the rover **autonomously** map the distribution of water/hydroxyl in its environment

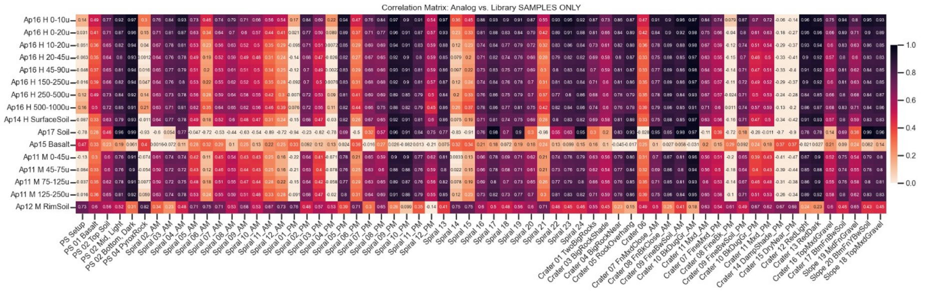
Background on Previous Spectra-Spatial Characterization

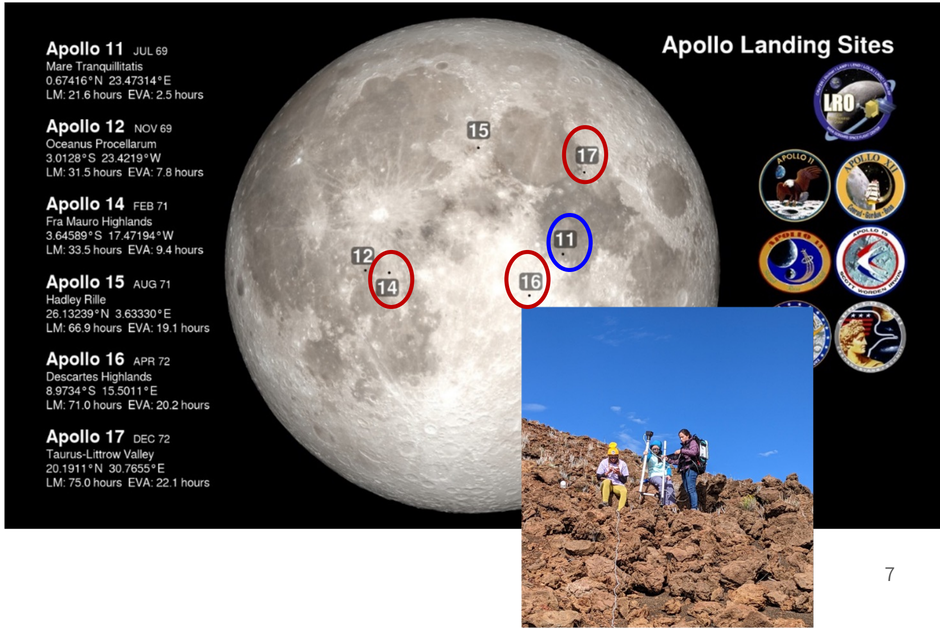
Purpose: evaluate the likeness of the Big Island as a lunar surface analogue

Method: spectra-spatial investigation with a visible and near-infrared (VNIR) spectrometer

Product: correlation matrices

Conclusion: the spectral measurements in the analogue are not consistent; **It is possible to discern which analogue measurement has the highest similarity to any lunar returned sample by correlation coefficients.**

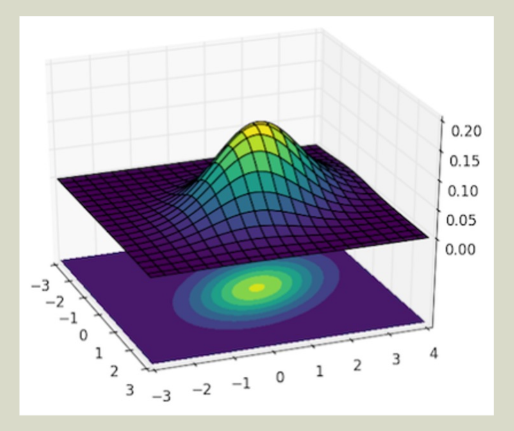


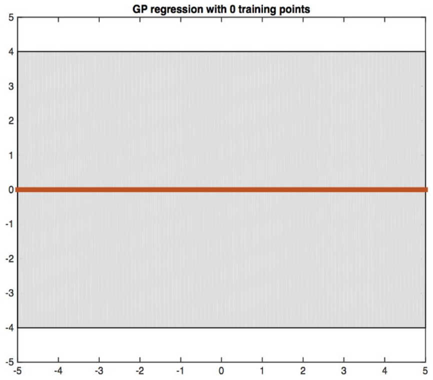


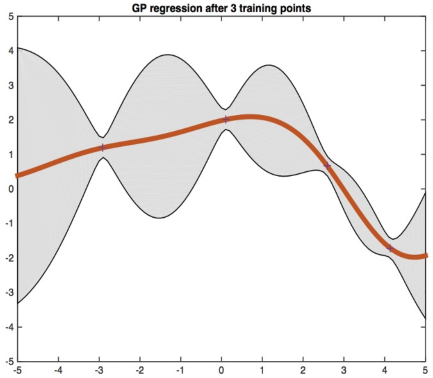
[1] Wang H. et al. (2023) Aerospace Research Central, 1-24.

Background on Gaussian Process Active Learning

- Autonomous Robots for Space Exploration
  - Information Exchange, Performance Differences between ML Algorithms, Testing Environments
- What is a GP?
  - A process in which a finite set of random variables has a joint Gaussian distribution
- Experimental Procedure
  - Load Environment
  - Define Exploration Strategy
  - Define Hyperparameters
  - Initialize Agent’s Starting Location
  - Seed Training Data with 10 Points
  - Explore the Surface

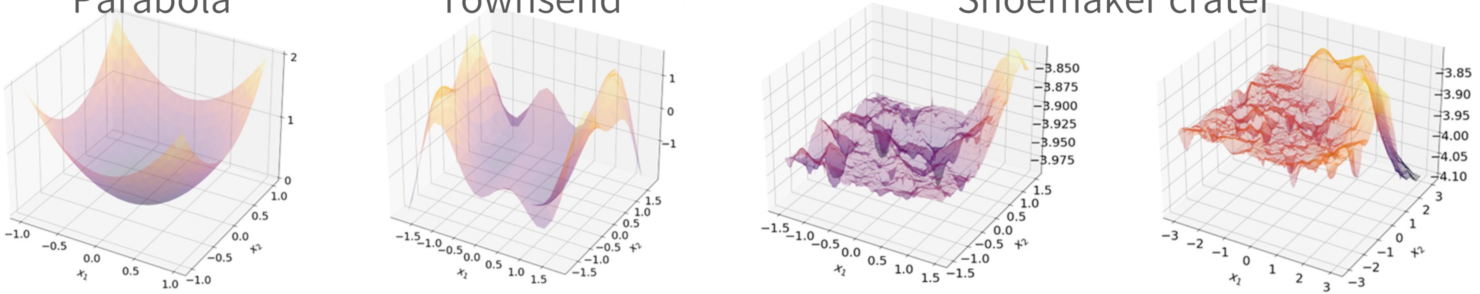






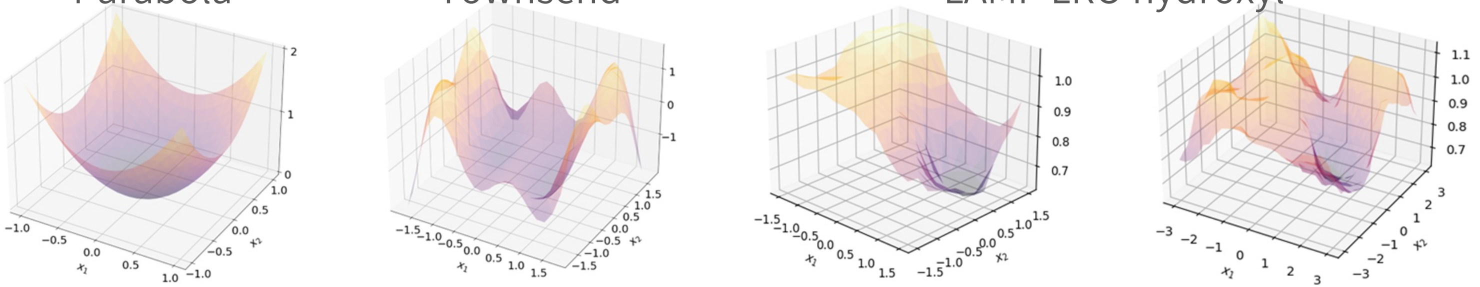
Background on Gaussian Process Active Learning

Parabola Townsend Shoemaker crater



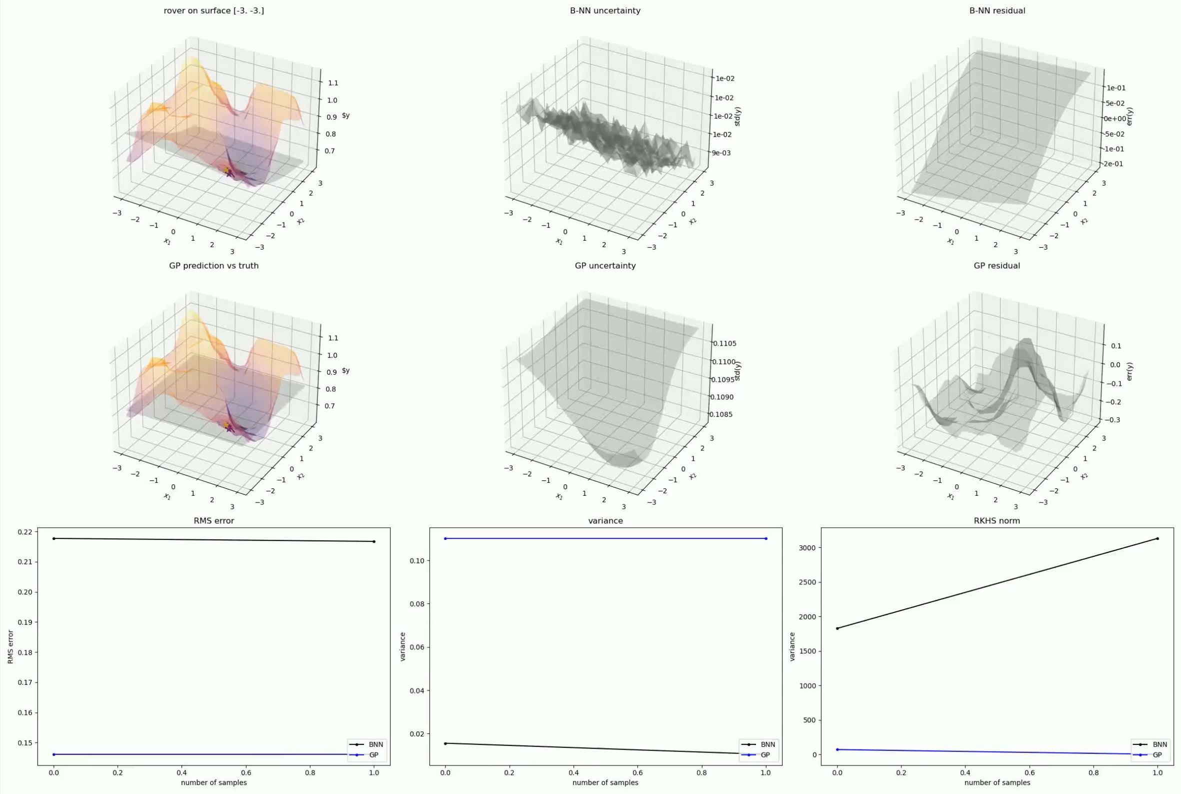
Surface environments the agent traverses

Parabola Townsend LAMP LRO hydroxyl



True value of target outputs the rover learns

Background on Gaussian Process Active Learning



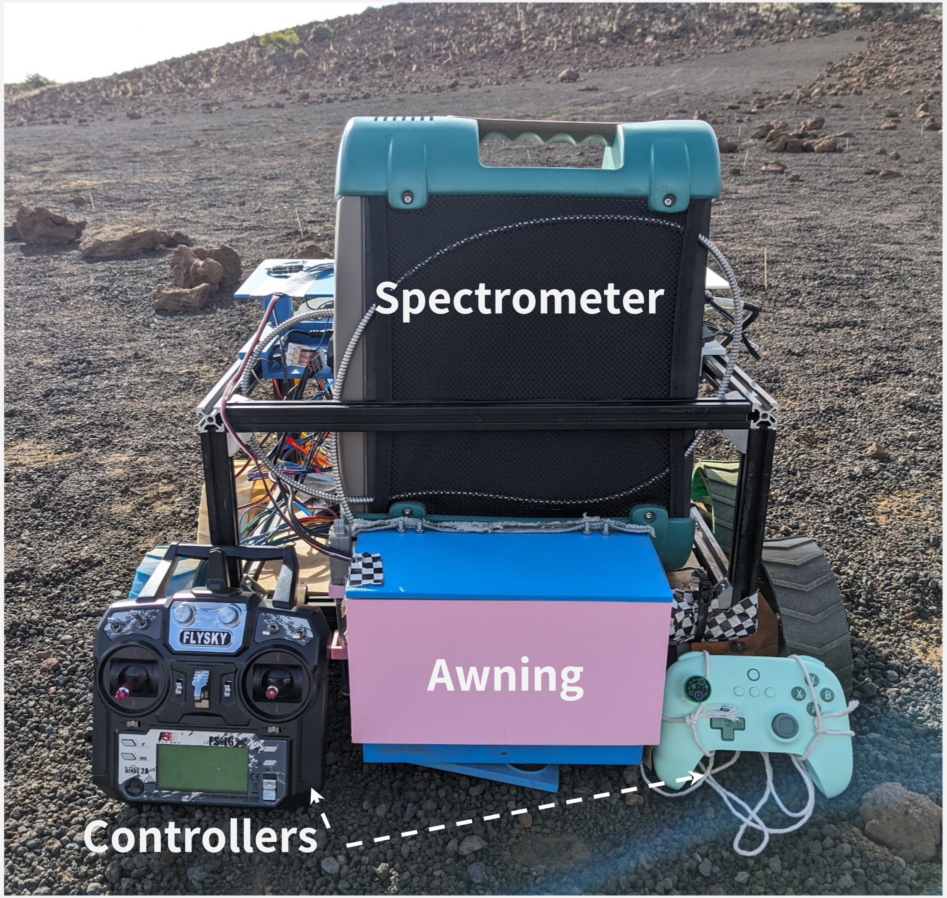
Analysis & Results

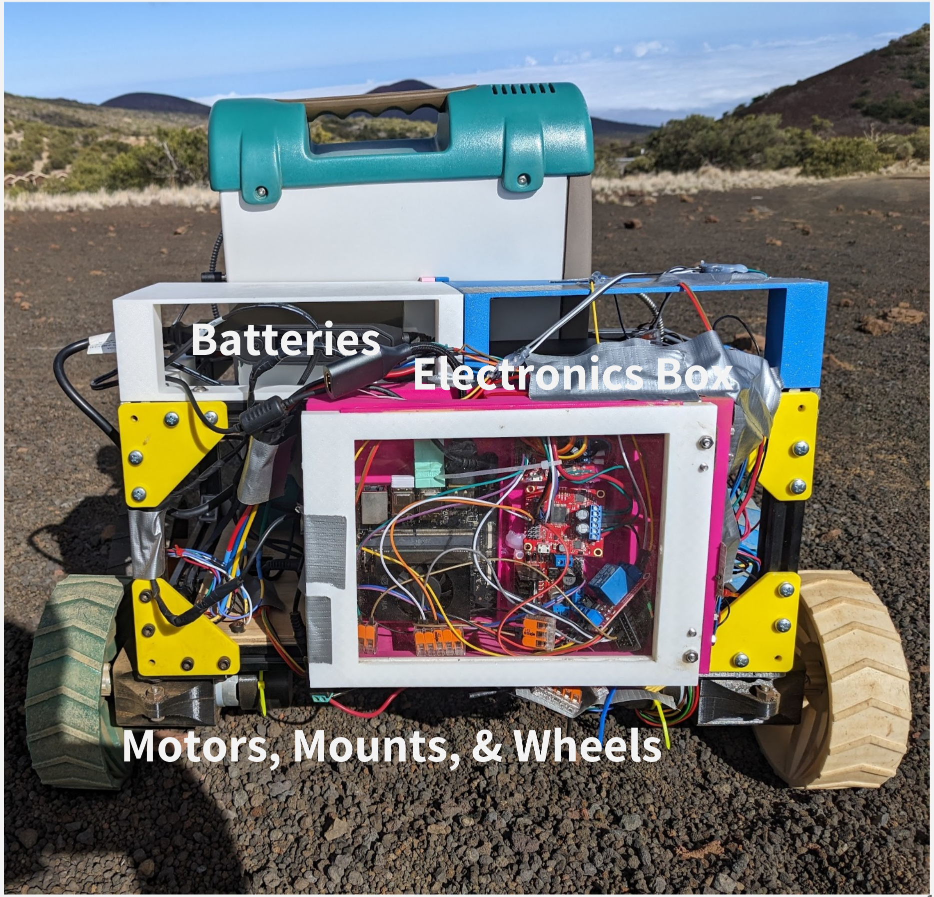
- The GP model required less time to train the model with higher accuracy and less samples than the BNN model
- The GP model was the most accurate in identifying the surface's true minimum location

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

Hardware Overview

Light Source: Halogen Bulb @ ~3050K; 900 Lumens





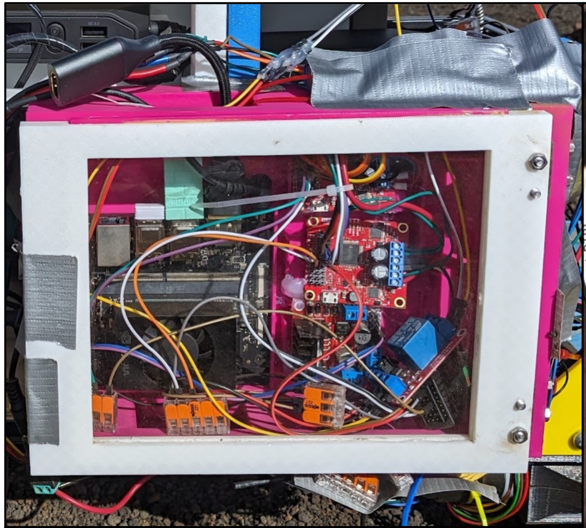
Specifications of Electronics

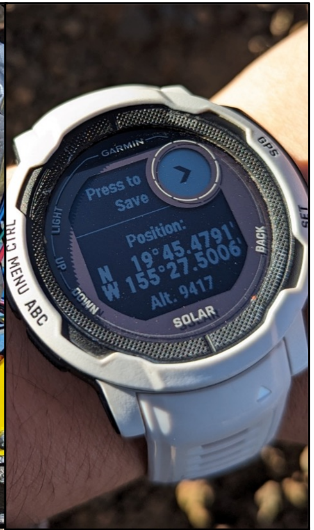
Electronics:

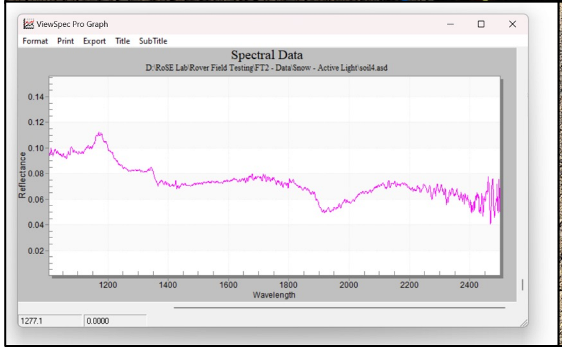
- Jetson Orin Nano Devkit (AI capable computation)
- Halogen Lamp & Relay (using ~10W power, rated for 50W)
- GPS (precision ~5-10 meters)
- Motors & controllers (ANNIMOS Servo, Roboclaw motor controllers)

Data Products:

- Spectrometer Data (ASD Files)
- Image Data (Taken on phone)
- GPS Data (Taken with watch GPS)



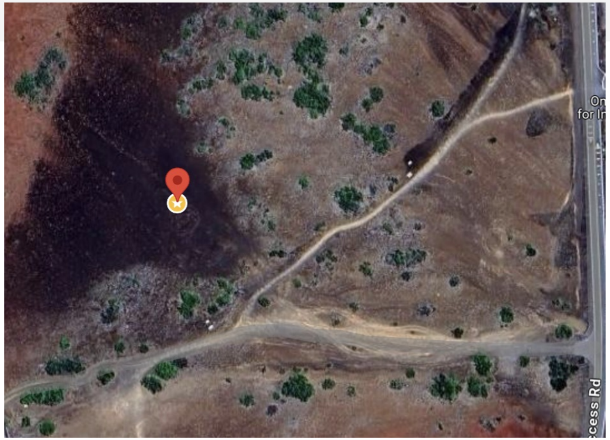


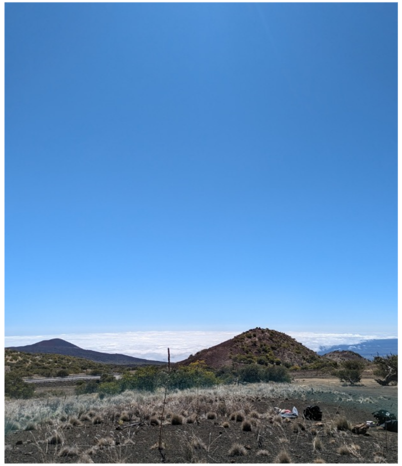


Experimental Campaign

Mauna Kea from Mar 18 - Mar 22

- Ran 7 tests
  - 2 ground truth trials [snake]
  - 5 active learning trials [various kernels]
- Grid size: 11x11 square [121 points; 484m^2]
- GPS Coordinates: N 19°45.4791 W 155°27.5006

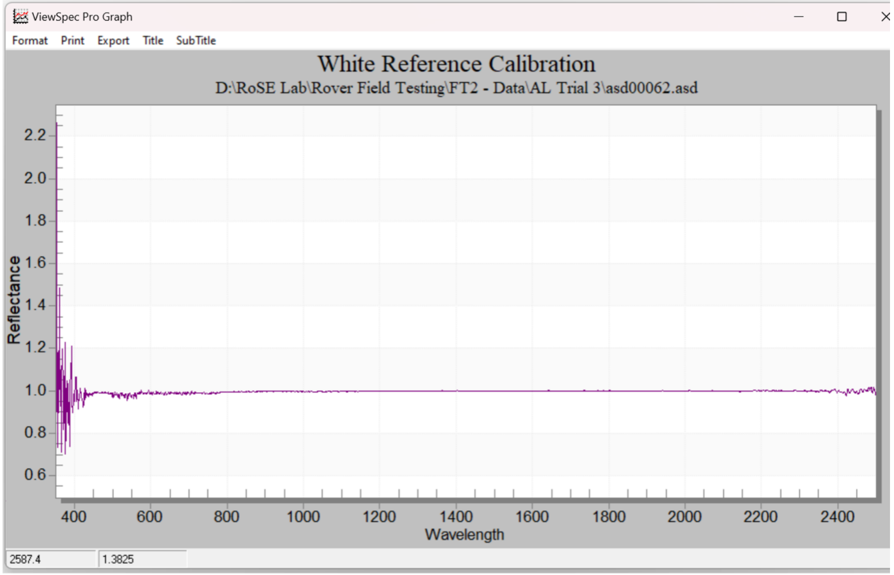




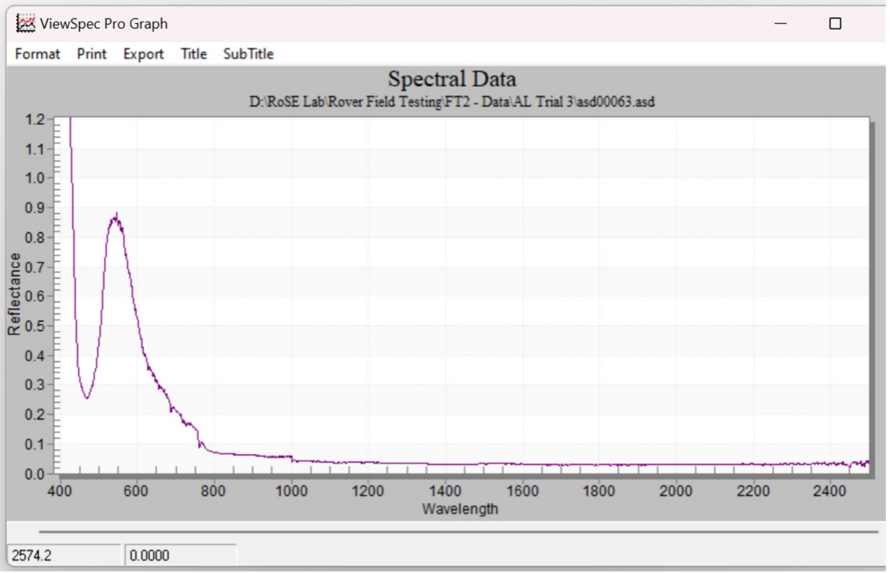
Experimental Campaign

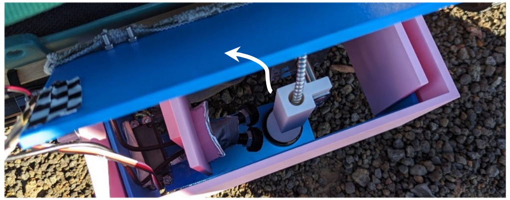
Sampling Operations per Spot

1. White Reference for Spectrometer



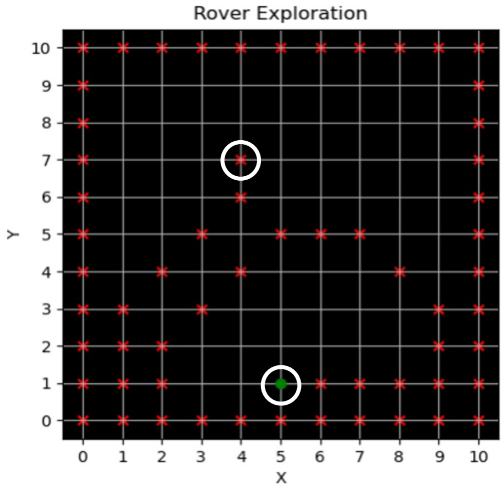
2. Remove WR & Take Spectral Meas.





Sampling Operations per Spot

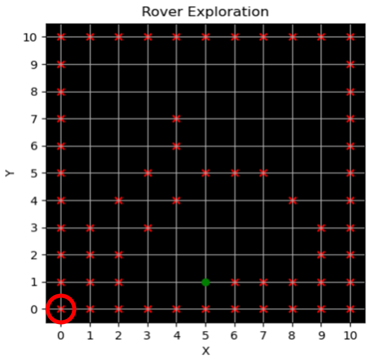
3. Run Code to Process Data
   - Process Spectra through ViewSpec Pro
     - ASCII Export > Reflectance > Print Header Information
   - Correlation data
   - Waypoint data

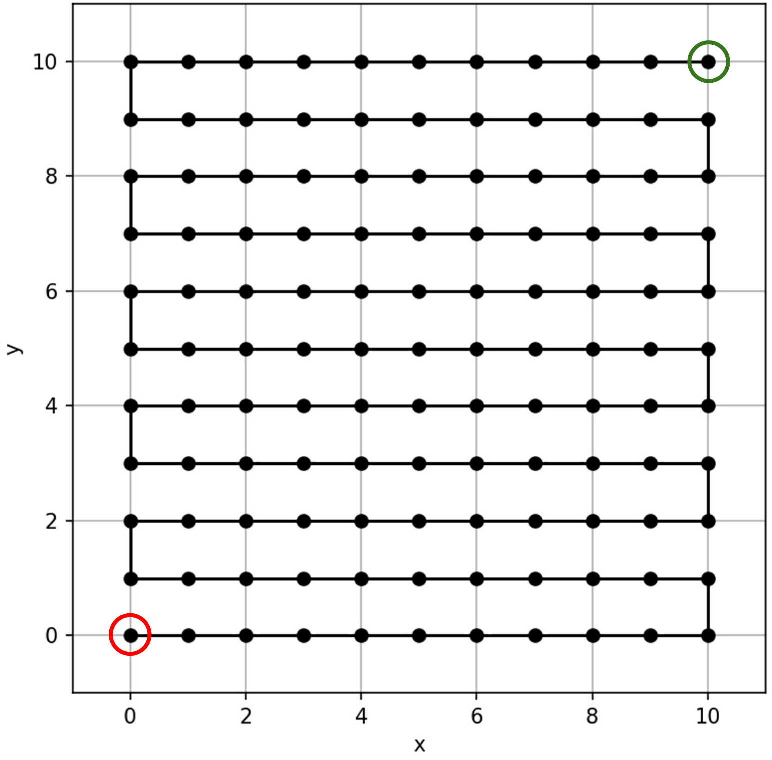


4. Move to Green Point & Repeat!

Ground Truth Generation

- 11x11 grid with a 2 meter discretization
- Collected in snake pattern
- Spectral measurement was taken at each point
- Correlation was calculated between the bottom left corner (0,0) spectra





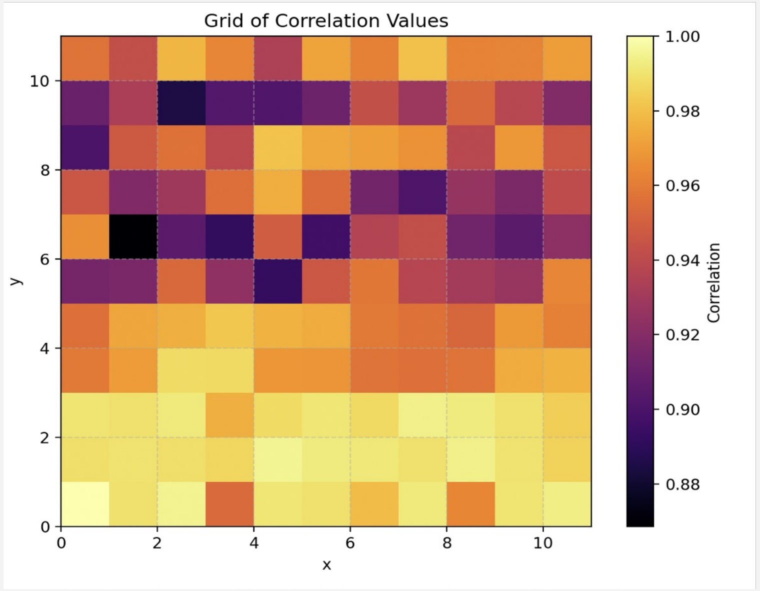
Machine Learning Implementation

- Gaussian Process Active Learning Algorithm
  - Matern Kernel
  - Correlation values retrieved from the (0,0) Spectra

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}

- AL models tend to be more sample and distance efficient in proposing trajectories while offering model convergence as compared to science blind methods
  - Verified this in simulation, now moving to real-world application



(0,0) Reference

Software Architecture for Field Testing GPAL Algorithm

Collect and Process Sample

White reference and spectra save **(ASD file)** using RS3 software

Utilize pyautogui to automate processing ASD -> text files using ViewSpecPro software ("tab" activates process)

Calculate Correlation

Use spectra text file to calculate correlation to reference file (Apollo or (0,0) spectra)

Spectrometer Data

Updated Model

Correlation Number

Waypoint

Gaussian Process Active Learning Algorithm

Add grid coordinate point to x_train
Add correlation number to y_train

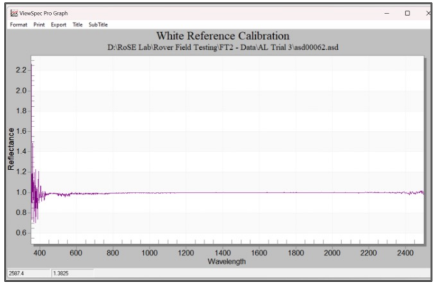
Retrain model using new x_train and y_train

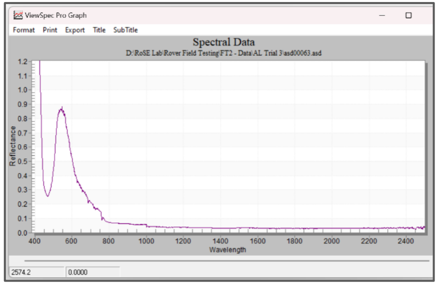
Evaluate GP model for confidence bounds and calculate uncertainty (uncertainty = upper - lower bound)

Proposes and displays (matplotlib) nearest neighbor coordinate with the highest uncertainty

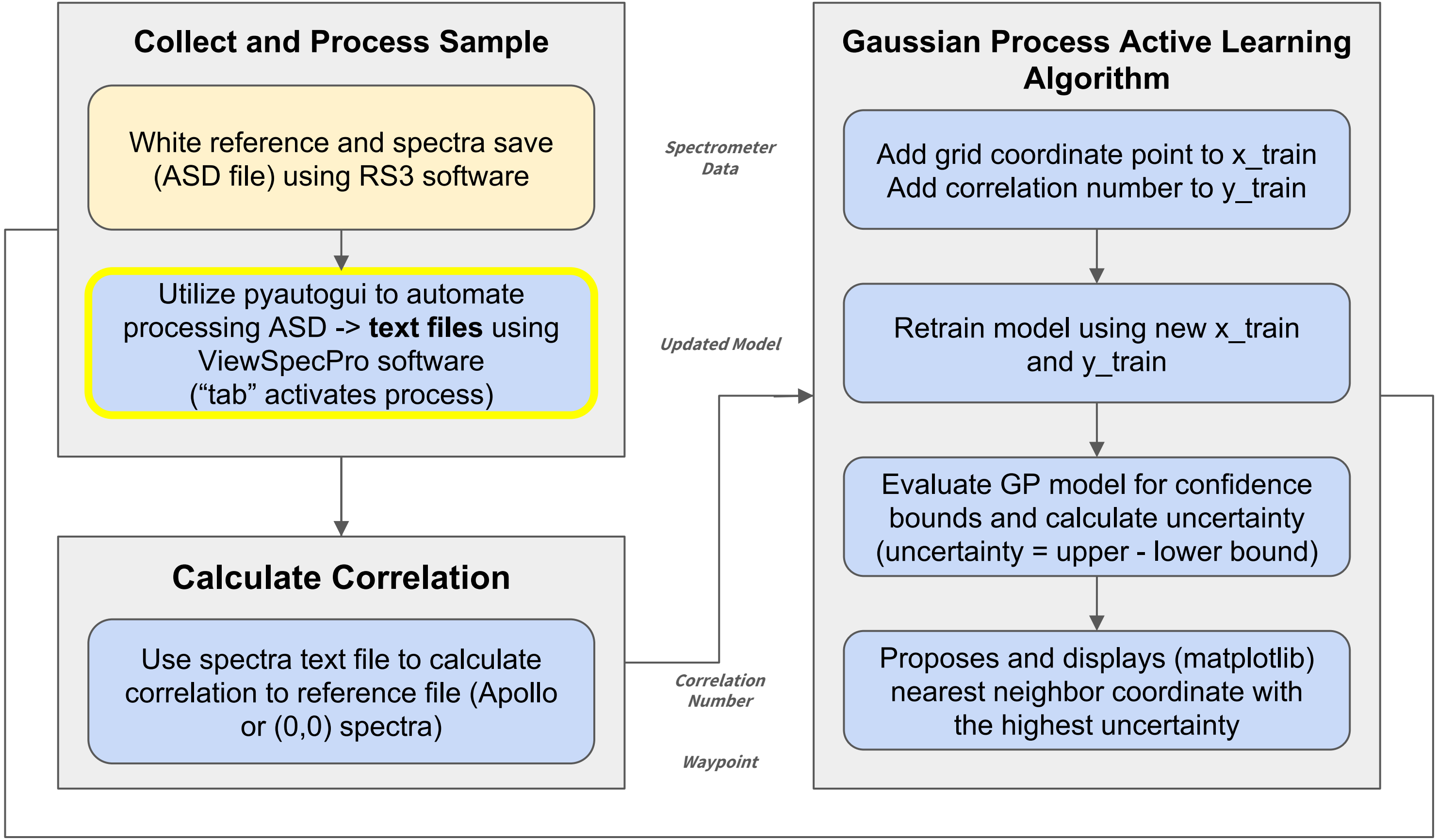
RS3 Software (Manual)

Field Testing Code (Auto)





Software Architecture for Field Testing GPAL Algorithm



RS3 Software (Manual)

Field Testing Code (Auto)

Example .txt file data

Wavelength	asd00000.asd
350	7.73733821537864
351	9.00554398047202
352	9.16924947112074
353	8.90135910630817
354	7.2013699706968
355	6.68568808833797
356	7.93816387914794
357	7.38320907131274
358	9.15295271837116
359	12.7507624427325
360	12.0749777326485
361	10.465932997854
362	8.32434348043976
363	7.73930455593183
364	10.4182501835677
365	11.1219176699201
366	16.3171941134116
367	35.9085999449558

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Collect and Process Sample

White reference and spectra save (ASD file) using RS3 software

Utilize pyautogui to automate processing ASD -> text files using ViewSpecPro software ("tab" activates process)

Calculate Correlation

Use spectra text file to calculate **correlation** to reference file [(0,0) spectra]

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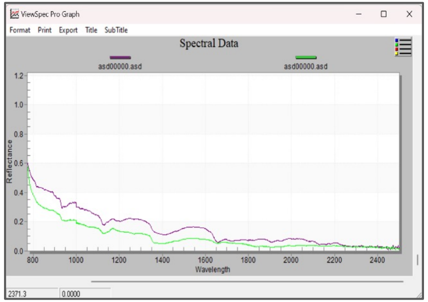

Green = (0,0) spectra
Spectral Correlation: 0.923903032002655

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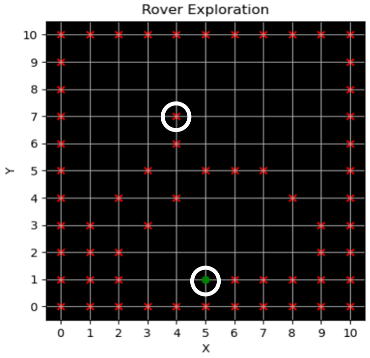

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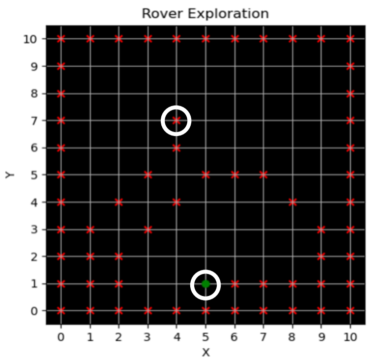

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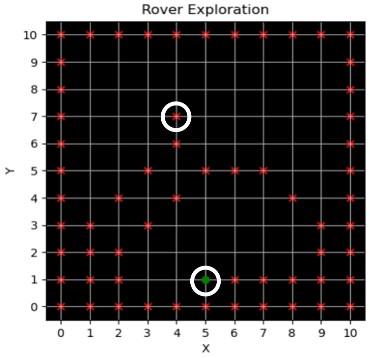

Software Architecture for Field Testing GPAL Algorithm

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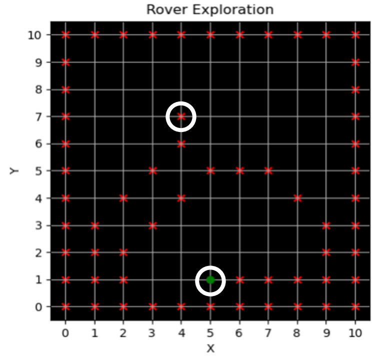
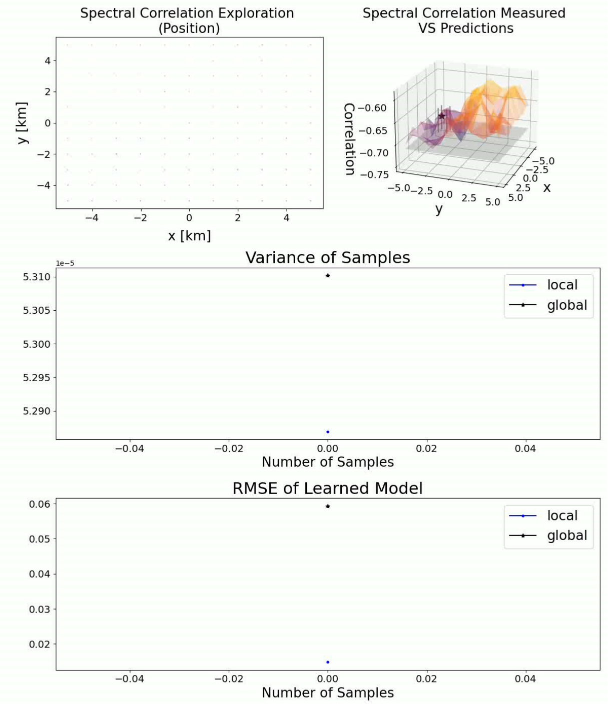
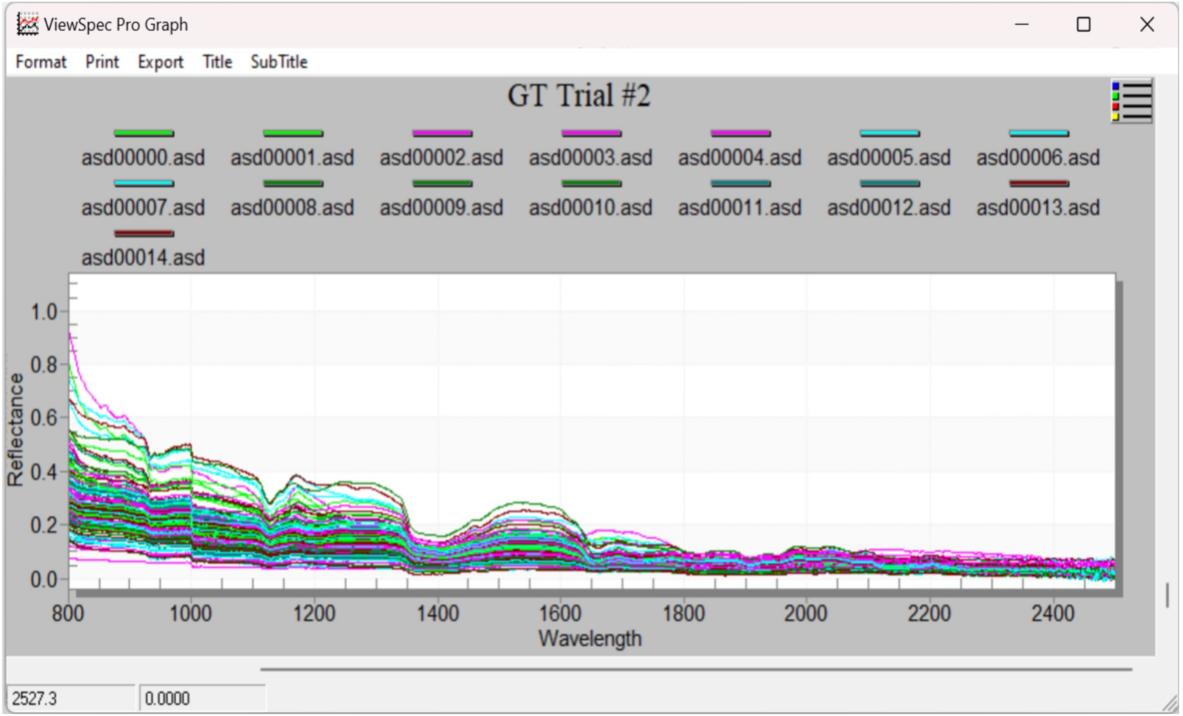


GT Trial #2 [Matern Kernel]

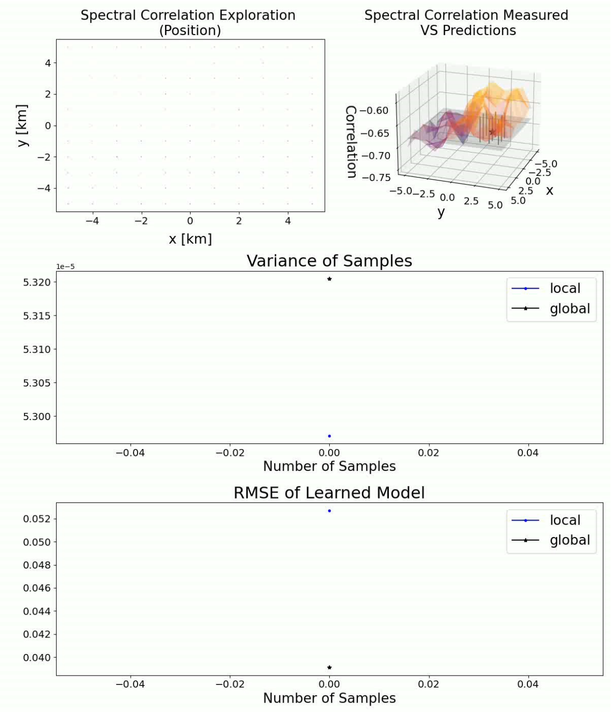


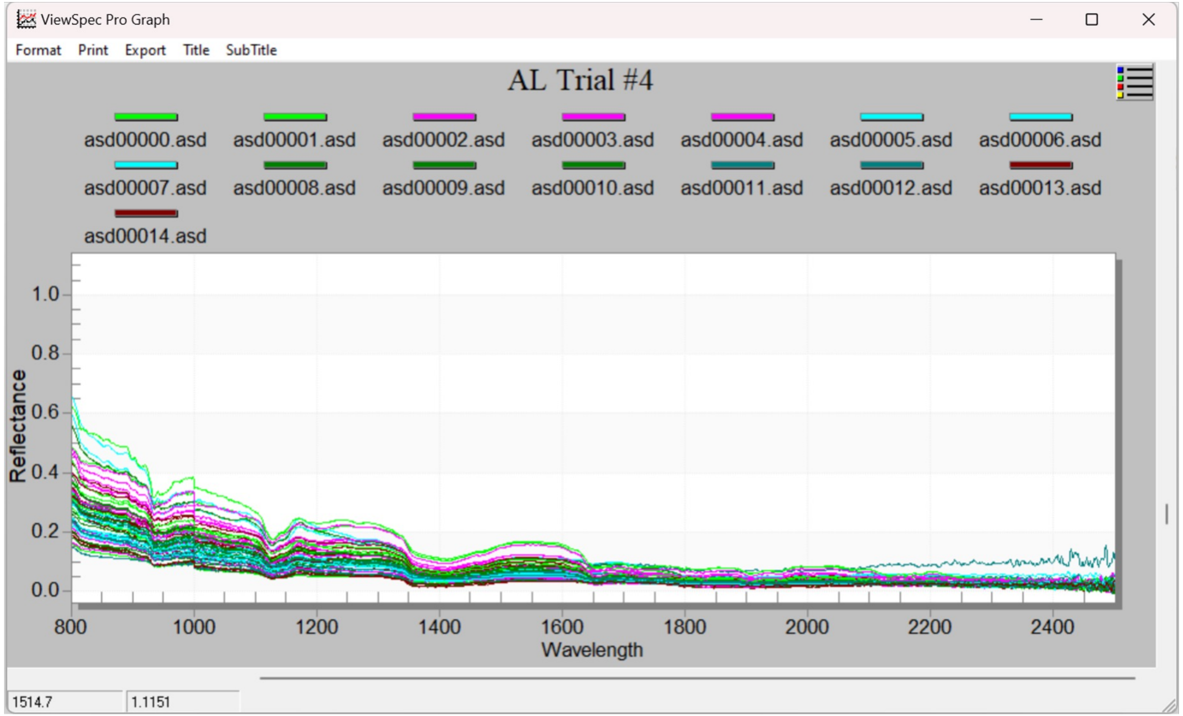


Converges in 104 samples to 0.0227 RMSE

This trial is utilized as the Ground Truth (GT). The rover's movement is considered to be Science Blind.

AL Trial #4 [Matern Kernel & (0,0) Spectra Correlation]





Converges in 49 samples to 0.0255 RMSE

Conclusion & Future Work

- Moving small steps forward towards rover autonomy in a real environment traceable to a lunar space mission
- **Performance difference between AL vs SB methods**
  - AL converges in ~half as many samples, traveled to 49 points instead of 104, RMSE at convergence would have been lower if data collection was the exact same as that found during the GT Trial
- Improve the rover design & operations
  - Improve the spectrometer integration to allow for better data collection [decrease noise]
  - Limit human operation of the rover’s mechanical functions
  - Test the rover in an environment where it would be required to map out water distribution with its ML algorithm

Thank you!

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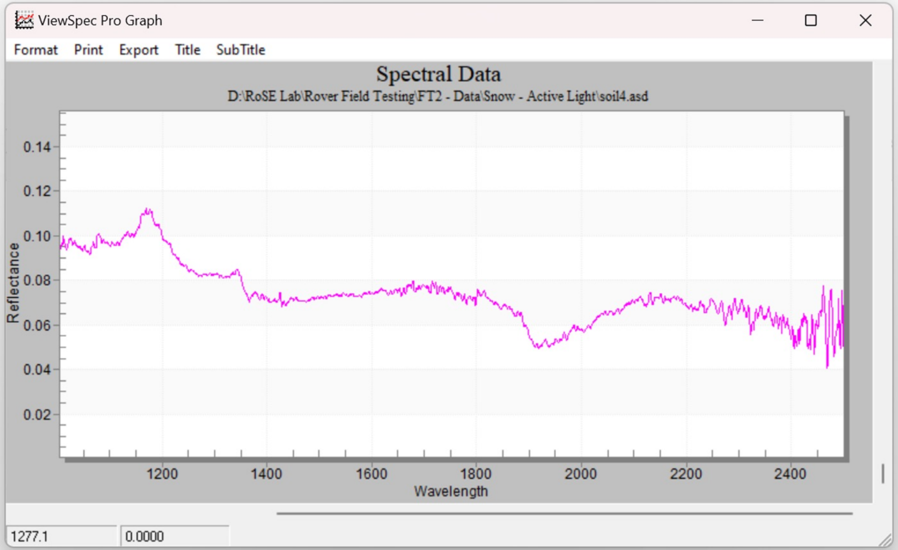
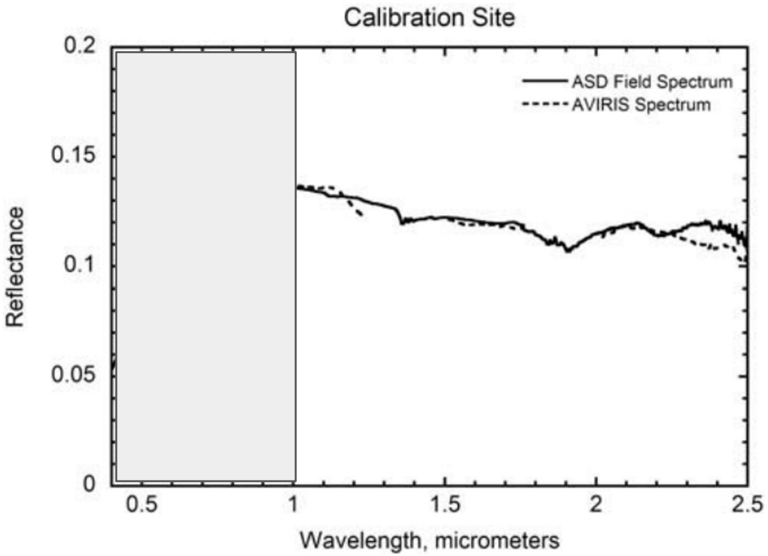
References

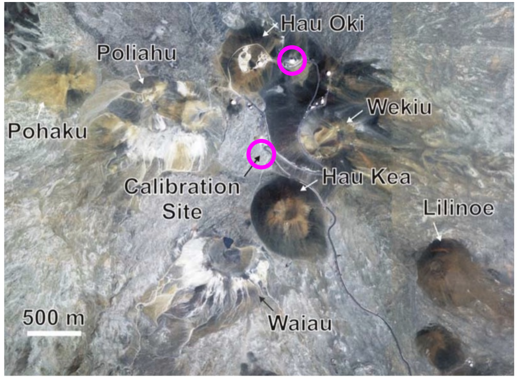
[1] Wang H. et al. (2023) Aerospace Research Central, 1-24.
[2] Akins S. and Zhu F. (2023) Aerospace Research Central, 1-15.
[3] Kate I. L. et al. (2013) Journal of Aerospace Engineering, 1-14.
[4] Guinness E. et al. (2007) Journal of Geophysical Research, 1-14.





Expectation vs. Reality

Spectral Measurements



[Hyperspectral reflectance mapping of cinder cones at the summit of Mauna Kea and implications for equivalent observations on Mars]

Quality of Spectral Measurements