INTELLIGENT MAPS FACILITATE AUTONOMOUS KILOMETER-SCALE SURFICIAL SURVEY IN ROVER TESTS AT AMBOY CRATER.

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Introduction: Often teleoperation of planetary exploration robots is infeasible due to low communications bandwidth and infrequent command cycles. Under these circumstances onboard analysis can improve the quality of returned science data. Autonomous agents can explore continuously, identify informative features for measurement, and select preferred data to transmit [1]. Many such systems can benefit from an awareness of spatial relationships in data. For example, a rover performing site survey should avoid unnecessary measurements that oversample a single homogeneous unit. Formally, the automatic exploration decisions should respect correlations in data due to spatial proximity as well as remote sensing.

We have developed an autonomous surficial mapping system based on a multi-tier spatial model that combines remote sensing and *in situ* measurements. This *intelligent map* is a statistical model that extrapolates from previous data and infers the likely result of future measurements at any location in the environment. This allows the agent to adapt its survey path, exploiting spatial and cross-sensor correlations to improve efficiency. The map's prediction uncertainty defines the information value of candidate observations in accordance with formal principles of Bayes-optimal experimental design [2]. Rover tests at Amboy Crater, California (Figure 1) demonstrate a geologic site survey that maps surface material with Visible Near-Infrared (VIS/NIR) reflectance spectroscopy.

Algorithm: Our current work applies the intelligent map approach to the specific problem of geologic site survey. Here a rover travels in a predefined "exploration corridor" toward an end-of-day goal location, mapping surface materials *en route* (Figure 2). A Gaussian process model [3] addresses the regression problem of mapping spatial locations [*lat, lon*] and orbital sensing bands [$c_0, \ldots c_n$] to a scalar value representing observations of surface material. The observations y are perturbed by Gaussian noise ϵ.

$$y = f(lat, lon, c_0, \ldots c_n) + \epsilon, \quad y \in \mathbb{R},$$

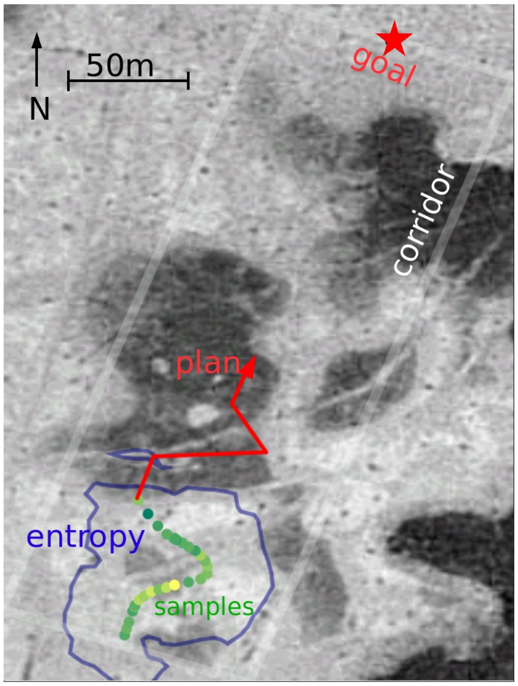
The explorer agent learns model parameters on the fly in order to discover and exploit correlations in data. The information value of a new observation is proportional to its entropy [2], e.g. our remaining uncertainty about the prediction y given learned correlations among previous spectra and remote imagery.

At regular 3-minute intervals an onboard planning algorithm [4] evaluates candidate paths to the goal, simulating future observations and computing their information value. The rover follows the path which yields the best expected improvement in map fidelity that can still reach the end-of-day goal within the traverse's prespecified time budget.

Figure 1: The Rover "Zoë" approaching a patch of basalt in Amboy Crater.

Rover Platform and Instrumentation: Zoë (Figure 1) is a solar-powered field robot developed at Carnegie Mellon University to test remote science operations involving long-range navigation [5]. It is 2m in length and can sustain velocities of 1m/s. Mast-mounted navigation cameras provide stereo vision for obstacle avoidance. The instrument package includes an ASD FieldSpec Pro VIS/NIR reflectance spectrometer that can collect data from distant solar-illuminated targets. The spectrometer's objective lens has a 1 degree field of view; it is mounted to the rover mast on a pan-tilt servo unit. A white reference calibration target mounted to the deck compensates for lighting changes during reflectivity calculations. The spectrometer aims at a fixed -30 degree angle of declination at the ground directly in front of the rover. We acquire spectra at 7-second intervals during forward motion to get periodic measurements of surface material.

The spectra at our field site describe mixtures of two basic physical materials: sediment and basalt. Thus the spectras' intrinsic dimensionality is low. Reflectance spectra of macroscopic mixtures generally combine linearly [6], and linear dimensionality reduction recovers the principal distinction. We project spectral measurements onto their first principal component to yield the scalar observation y. The Gaussian process learns to infer this value based on physical location and data from a USGS Digital Orthophoto Quadrangle (DOQ), a visible-spectrum overflight image with approximately 1m/pixel resolution.



notations show the rover status during an autonomous traverse. Colored dots show spectral samples collected along the rover path. The blue line indicates an isocontour of the prediction entropy. The red line shows waypoints in the current plan.

Field Tests: Amboy Crater is a basaltic lava flow located in the Mojave Desert in California (Figure 1). It consists of vesicular pahoehoe lavas that may be analogous to surfaces on the Moon and Mars [7]. Our tests focus on the east edge of the Amboy lava flow where eroded basalt contacts a sediment-covered playa region. The two distinct types of surface material, sediment and basalt, correspond roughly to patches of light and dark albedo visible in the overflight image of Figure 2. Here the survey task is to map the distributions of the two materials.

We consider a map from single exploration corridor 300 meters in length (to appear in [8]). This trial used a 16 minute time allowance. Figure 2 shows DOQ overflight imagery of the traverse area. Annotations illustrate the rover's navigation plan after collecting the first 27 spectral samples. The planning algorithm chooses paths that cover the principal units of surface material within the corridor while respecting the time budget. The blue line indicates one isocontour of the prediction entropy; areas beyond this line have high prediction uncertainty which makes them good sites for future observations. For example, in Figure 2 the basalt patch's entropy is high because no sample from this area has been collected.

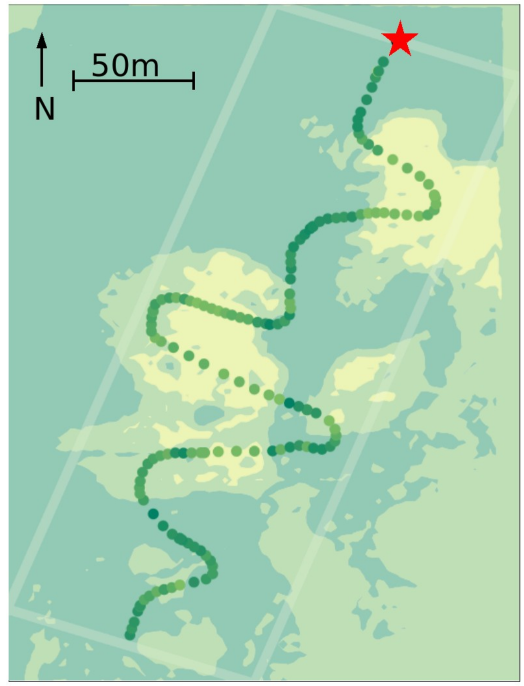


Figure 3: Resulting map of surface material. Gaussian process inference extrapolates from sparse samples by leveraging remote sensing and proximity correlations. The rover dynamically adapts its path to visit areas for which predictions are uncertain, and ignores the homogeneous area to the upper left.

The map resulting from the completed traverse appears in Figure 3. This final inference result shows the autonomous terrain classification: yellow areas correlate with dense basalt and green corresponds to a prediction of the sediment spectrum. The prediction is most certain – and accurate – within the corridor near the rover's path. The complete Amboy crater experiments include trials at other locations with additional data products [8]. Future work will continue analyzing these results to quantify system performance. However, these preliminary tests demonstrate adaptive surficial mapping that leverages kilometer-scale data from *in situ* and remote sensors.

References: [1] Castaño R. L. et al. (2003) *Intl. Conf. Machine Learning.* [2] M. Shewry et al. (1987) *Journal Applied Statistics*, 14:2. [3] Williams, C. K. I. and Rasmussen, C. E. (1996) *Neural Information Processing Systems*. [4] Checkuri, C. and Pal, M. (2005) *IEEE Symposium on Found. of Comp. Sci.* [5] Wettergreen D. et al. (2005) *ISAIRAS XIII.* [6] Mustard, J. F. et al. (1986) *LPSC XVII.* [7] Greeley R. and Iversen, J. D. (1978). *Field Guide to Amboy Lava Flow, San Bernardino County, California.* [8] D. R. Thompson and D. Wettergreen (2008) i-*SAIRAS XIV* (to appear).