AUTOMATED TARGET SELECTION FOR OPPORTUNISTIC ROVER SCIENCE

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Introduction:

A number of remote sensing instruments on rovers have a very narrow field-of-view and thus require selection of specific targets for sampling. Such instruments include mini-TES, LIBS, and infrared point spectrometers. The typical scenario for selecting targets for these instruments is to manually select the goal points using data that has been previously downloaded. This means that targets can only be selected based on the rover site at the beginning of an upload command sequence (for which data has already been downloaded). After a rover traverse day, samples from the new site can be collected by 'blindly' targeting the instrument. If conditions are fortuitous, this can save time by acquiring samples one sol sooner, rather than selecting targets for the following sol based on downloaded imagery. During a traverse, samples from these instruments can only be collected using blind sampling.

In this work we describe the development and demonstration of a system that can identify opportunistic targets and collect data on these targets. There are a variety of autonomous rover capabilities currently in development for future in-situ missions. One key capability, autonomous onboard science, continues to grow in importance as rover travel distances continue to dramatically increase. OASIS [1], an Onboard Autonomous Science Investigation System, is a JPL-managed project designed to maximize mission science on rover missions with long traverses. Within OASIS, we have implemented a method for automatically selecting rock targets for sampling and for collecting the targeted data during or at the end of a traverse. This could be used, for example on the future Mars Science Laboratory (MSL) rover to select targets for the ChemCam instrument (which includes a LIBS) to sample.

Two scenarios for selecting targets are being explored. In the first scenario, an image is taken and analyzed onboard. Regions in the image represent ting rocks on the surface are identified, and points from one or rocks are selected as targets for other instruments. In the second scenario, an image is taken and analyzed, but in this case in addition to identifying the location of rocks, some properties of the rocks are estimated and a priority for the rock targets is determined based on the extracted properties and prior inputs from the science team. The second scenario is most useful when there are more rocks in a scene than can immediately be analyzed.

Approach:

The approach is to first identify the rocks in te scene using the rock finder in the feature extraction component of the OASIS system [2]. Points on these identified rocks are then selected for targeting (Figure 1). Note that this problem is distinctly different from accurately determining the outline of a rock as the result is the selection of a single point on each rock.

The performance of the automated target selection algorithm was compared to two baseline methods. The first baseline method is a binary thresholding on a grayscale image. The grayscale image was formed by taking the first Principle Component of the three band color image. The best threshold for each image was determined by selecting the threshold that gave the highest percentage of pixels selected as actual rocks, i.e. $\max\left(\frac{\#\text{ rock pixels} > \text{threshold}}{\#\text{ pixels} > \text{threshold}}\right)$. This was performed using images in which all the rocks had been manually labeled. While this method of determining the threshold could not be used onboard, as it uses knowledge of the location of the rocks in the image to estimate a target, the implementation does provide an upper bound on the thresholding approach.

The second baseline method that was compared against our target selection was to use the three-band color image to determine which points belong to rocks and which were not. For this method, the K-means clustering algorithm was used. We performed the analysis for K = 2, 3, and 4. Here we present results for k = 2.

Results:

The automated target selection method was tested on a set of 65 images formed from the full color 360° panorama taken by the Spirit Mars Exploration Rover at the Legacy site. For this test, the top five target points were selected for each image. Using the automated target

selection, 92% of the points selected as targets correspond to rocks in the scene. 257 out of the 285 targets selected in the data set were rocks. Of the 28 misses, 16 were of rover tracks (Figure 2) and 7 were near misses where a shadow near the rock was selected. The scene has a 12% cumulative fractional area covered by rocks and thus random sampling would yield 12% of the points as rocks. Thus, the automated targeting method results in a nearly a 9X increase in acquiring samples of desired targets (rocks) over blind targeting.

For the thresholding method the average number of correct (rock) pixels per image for the Legacy panorama was 76%, however some images had very few pixels meeting the best threshold criteria. Thus, while the average correct percent of pixels per image was 76%, considering all pixels in the image set that meet the criteria specific to the image to which they belong, only 28% of the overall pixels designated as rocks actually belong to rocks.

In initial testing of the k-means algorithm on 10 of the images in the Legacy panorama has been completed. For this experiment, k-means clustering was run with two classes (k=2) on each image using the red and blue bands. Since k-means is unsupervised, the class with the highest percent correct was selected to be labeled as rocks. This could be done onboard as it is always the class with the fewer number of pixels. The average percentage of pixels correctly identified as rock was 38%.

Planning and Scheduling:
Once the data analysis software has identified a set of new science targets, these targets are passed to onboard planning and scheduling software that can dynamically modify the current rover plan in order to collect the new science data. This component takes as input the new set of science requests, the current rover command sequence (or plan), and a model of rover operations and constraints. It then evaluates what new science tasks could be added to the current plan while ensuring other critical activities are preserved and no operation or resource constraints are violated. Planning and scheduling capabilities are provided in OASIS by the Continuous Activity Scheduling, Planning and Re-Planning (CASPER) system [3]. The system is capable of retargeting as well as driving to an identified target. To evaluate our system we performed a series of tests both in simulation and using rover hardware in the JPL Mars Yard, successfully demonstrating the benefits of the concept.

References: [1] Castano, et al., *IEEE Aerospace*, (2006). [2] Castano, el al., *IEEE Aerospace*, (2005). [3] Chien, et al, *AIPS* (2000).

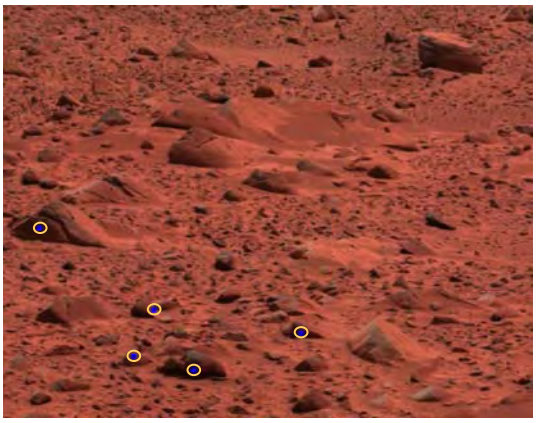

Figure 1. Candidate instrument targets automatically selected in MER Pancam Image from Legacy site. All five of the automatically selected targets are rocks. The expected number of blindly selected rock target points is less than one of five. Only points within 9m of the rover were considered as this is the range of the ChemCam instrument.

Figure 2. Candidate instrument targets automatically selected in Legacy Pancam image with one miss. Four are correctly rocks, while one is a site in the disturbed soil of the rover track. Note that the selecting the largest rocks was not a criterion.