Using Scaled Visual Texture For Autonomous Rock Clustering:

R.C.Anderson[1], R. Castano[1], T. Stough[1], V. Gor[1], and E. Mjolsness[1], Jet Propulsion Laboratory, Pasadena, CA 91109, robert.anderson@jpl.nasa.gov.

Introduction and Background: Future planetary surface exploration missions with mobile robotic platforms will have the capability to collect more sensor data than can be transmitted to earth. To maximize the return on these missions, it will be critical that the platforms have the capability to analyze information onboard and select data that is most likely to yield valuable scientific discoveries. As the platforms become more autonomous in their navigation, it would be desirable to be able to take advantage of opportunities that are encountered in real time. The goals of this project are aimed at increasing the science return on such missions by developing algorithms for onboard detection and prioritization of science information collected by a rover. The approach is to analyze data that the rover can readily acquire and use such analyses to aid in deciding what information to send back to earth, where to take more samples using more time-consuming instrumentation, and which surface regions to explore further. The primary improvements in science return are smart selection of data to collect and return, with mobile science platforms.

Basic Ideas and Principles: There are many levels at which decisions can be made about which data is the most significant and where should further samples be taken. At one of the most basic levels targets must be identified in a scene. When people view an image, they naturally divide it into regions and associate the regions with specific objects. People are also adept at comparing objects that are at different distances from the viewer. Similar objects that are different distances to the viewer may appear quite different in terms of image pixels, but people are easily able to mentally scale the objects and make meaningful comparisons. We are developing methods that will enable a rover to have both of these capabilities in a limited capacity. In this area, we are specifically working on techniques to identify rocks in an image, to scale their image such that they are effectively viewed from the same distance, and then to compare them based on textural information.

Procedure:
- Find Rocks
- Texture Process Rocks w Stereo Information
- Scale each rock image chip to intermediate distance
- Calculate texture features for each chip
- Determine which features are valid
- High frequency features are invalid for scaled chips
- Cluster rock feature vectors to determine groups of similar rocks
- World Model: The rock image chips and their texture features will be incorporated into a world model which represents the area the rover is working in.
- Geological hypotheses can be tested on the resulting model.
- Rock type, frequency, and distribution can be calculated.

Rock Detector: Rock detection is composed of five components (**Figure 1**). The first two components, Edge-flow segmentation and surface density estimation, perform image segmentation, where the image is partitioned into different regions of similar color and texture. Edge-flow segmentation facilitates integration of color and texture into a single framework for boundary detection. Such segmentation identifies the direction of change in color and texture at each image location, and constructs an edge flow vector. By propagating the edge flow vectors, the boundaries can be detected at image locations which encounter two opposite directions of flow in the stable state.

In contrast, surface density estimation partitions the image into the areas of distinct density. These two segmentations are complimentary, since the first provides small and smooth segments, and the second produces large and jagged regions. Edge-flow segmentation results in image units for which attributes will be calculated, surface density estimation produces density map which will be used in calculations of segment density attribute.

Attribute calculation component calculates intensity, density and elongation attributes for each image segment (or region). Then spatially adjacent regions are merged based on density, and the attributes of new segments are recalculated. Finally, each region is classified into rock or background depending on region attributes, and results are reported to the user as an image of rocks and rock attribute table. Results for two images are shown in Figure 2.

Texture Processing: The texture processing step uses the output from the rock finder and the distance map from the stereo data to calculate distance invariant texture features for the rocks in the image. These texture features are used to cluster rocks into groups of similar texture within a given image and across images.

Eventually the texture features will be used to tag the rocks in a world model of the rover's surroundings. These features will allow us to determine the relative frequency of different groups of rocks in the area, to choose which rocks to examine more closely, and to form and test geological hypotheses about the rocks and their emplacement.

Regions from the rock finder are passed to the texture analysis component of our system and used to extract image chips containing individual rocks. Once the chips are extracted, stereo information is used to scale the rock image chip to an intermediate distance. We then calculate texture features for the image chip and determine which of those features are valid. The valid features associated with each rock are stored for further processing.

The texture features are produced using a Gabor wavelet decomposition which applies filters at different scales (frequencies) and orientations. The resulting feature vectors vary in length depenging on the size of the image chip. Our wavelet decompotition uses octavespaced filters over N scales (where N is the log base 2 of the image chip size). Therefore larger chips require more scales to decompose. An image chip which has been enlarged lacks the high frequency information present in chips which have not been; therefore, the high frequency features of enlarged image chips are invalid. If a chip has been scaled by a factor of 2 or less, one scale is lost; a factor of 4 or less invalidates 2 scales and so on.

The texture feature vectors are then used to cluster the rocks into groups of similar texture. The clustering is done with k-means using a modified euclidean distance metric. We cluster based on the texture features alone, and the addition of color information will improve the quality of our results. The number of clusters is presently selected using prior knowledge; however, we will use automated methods in our final system. The results of our initial experiments can be seen in Figure 3.

References.

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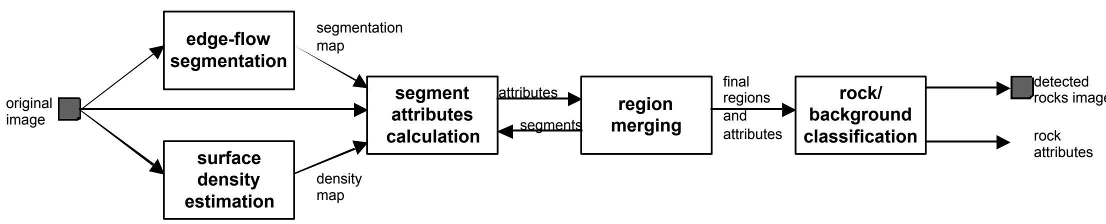

Figure 1. Rock detector. Image regions representing possible rocks, along with the attributes of these regions, are identified by the rock detector. The rock detector consists of five processing units that extract successive levels of information.

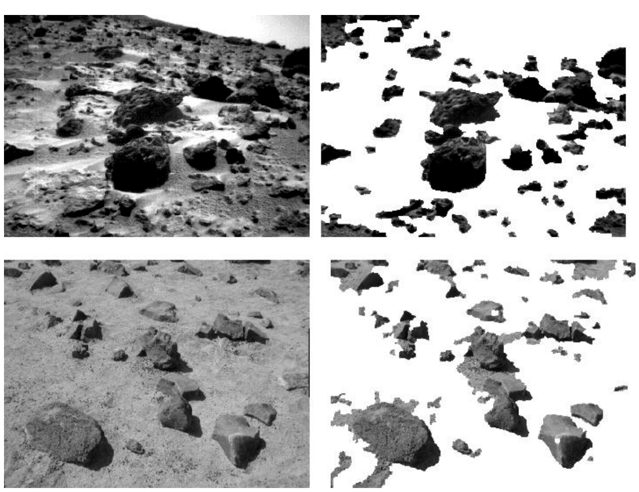

Figure 2. Rock regions detected. On the left are the original images (top: Mars Sojourner, bottom: JPL Mars yard). The right images show the regions that were identified as possible rocks.

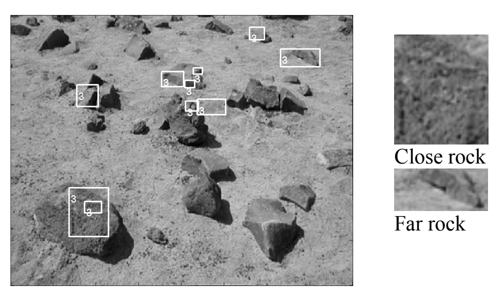

Figure 3. Clustered rock regions. After clustering the texture vectors, individual classes of similar rocks can be further examined. Here, one class has been extracted and the enlargements of two regions from this class scaled to the same distance are shown.