DEVELOPING AN AUTOMATED SCIENCE ANALYSIS SYSTEM FOR MARS SURFACE EXPLORATION FOR MSL AND BEYOND. V. C. Gulick[1], S.D. Hart[1], X.Shi[2], and V.L. Siegel[3]. [1] NASA Ames/SETI Institute, Mail Stop 239-20, NASA Ames Research Center, Moffett Field, CA 94035 (vgulick@mail.arc.nasa.gov), [2]UC- Santa Cruz, Computer Engineering Dept. School of Engineering 1156 High Street, Santa Cruz, CA 95604.

Introduction: We are developing an automated science analysis system that could be utilized by robotic or human explorers on Mars (or even in remote locations on Earth) to improve the quality and quantity of science data returned. Three components of this system (our rock, layer, and horizon detectors) [1] have been incorporated into the JPL CLARITY system for possible use by MSL and future Mars robotic missions. Two other components include a multi-spectral image compression (SPEC) algorithm for pancam-type images with multiple filters and image fusion algorithms that identify the in focus regions of individual images in an image focal series [2]. Recently, we have been working to combine image and spectral data, and other knowledge to identify both rocks and minerals. Here we present our progress on developing an igneous rock detection system.

We have been focusing on identifying rocks, autonomously, based on their color and texture (and eventually spectra) as measured from lab images of field samples. Initial work on our prototype image analysis system identified some igneous rocks from texture and color information [3,4]. For example, our texture algorithm successfully identified plutonic (crystalline, e.g., granite) from volcanic (noncrystalline, e.g., basalt) rocks with up to 90% reliability. Our color algorithm has been able to distinguish between felsic, intermediate, and mafic igneous rocks with up to 80% reliability.

When considering color only, using the weighted k-nearest neighbors approach [5], the algorithm correctly identified greater than 70% of the felsic rocks, at least 70% of the intermediate rocks, and greater than 80% of the mafic rocks. Using a similar approach for texture, the algorithm correctly identified 85% of the plutonic rocks and 76% of the volcanic rocks. We have used both Bayesian and Decision Tree automated reasoning approaches to combine the results of the color and texture algorithms. Based on our tests to date, the Decision Tree method has yielded better results, correctly identifying at least 80% of granites and granodiorites and greater than 70% of andesites and basalts using color and texture algorithms combined. In addition to the generally better performance, the Decision Tree method has the advantage of allowing one to trace the algorithm's line of reasoning in reaching a final identification. Since a hierarchical method more closely follows the line of reasoning used by practicing geologists, we feel it may meet with greater acceptance in spacecraft and field applications.

Spectral analysis algorithms have also been developed that successfully identify quartz, silica polymorphs, calcite, pyroxene, and jarosite from both visible/near-IR and mid-IR spectra [3,4]. We have also developed spectral recognizers that identify high-iron pyroxene and iron-bearing minerals using visible/near-IR spectra only. We have also initiated development of an overall integrated reasoning system that takes input from both image and spectral data [4]

To support this technology development effort, we have been building a combined image and spectral database of rocks and minerals with which to continue development and testing of our algorithms. Currently, we have collected, imaged and analyzed over 700 igneous, sedimentary, metamorphic rocks and mineral samples. Images are taken under controlled lighting and at fixed distances. We are in the process of obtaining Raman and visible, near- and mid-infrared spectra of the entire collection to help identify the minerals that comprise the samples. Analysis of both the physical properties and the relative mineral abundances of a sample form the basis of rock identification and classification. This extensive dataset allows us to optimize and test the algorithms under a variety of conditions. We will report on the current ability of our algorithms to identify and discriminate rock types with a variety of input data.

We envision that operation of an actual GFA in a field setting could entail covering a rock specimen with a hood at the end of a robotic arm or inserting the specimen into a self-contained field laboratory equipped with artificial lighting. Spectra and images of the sample would be obtained and the user (if available) would be queried for any human input. The system would then analyze the images and spectra autonomously or with additional human supervision. A top level reasoning system would then combine inputs from the image and spectral identifiers, human opinion, and any other data (e.g. geological maps, or data from other sensors) to render an opinion about the composition, texture, color and identification (rock classification) of the sample. The resulting high-level information would allow robotic (or a human) explorer to prioritize sample collection, recognize samples worthy of additional immediate study, or provide critical high-level information that can be used in the field to more efficiently guide field exploration. Such triage measures, by saving time and resources, could be invaluable when surface time or returned mass are important constrained resources.

References: [1] Gulick, V.C. et al. 2001 (2001) *JGR, 106,* 7745-7764. [2] Gulick, V.C. et al. (2000) *LPSC XXXIII*. [3] Gulick, V.C. et al. (2002) *LPSC XXXIV*. [4] Gulick et al. (2003) *LPSC XXXV*, [5] Gulick et al (2003*) Eos Trans. AGU, 84*(46), Fall Meet. Suppl., Abstract P41B-0407, 2003.