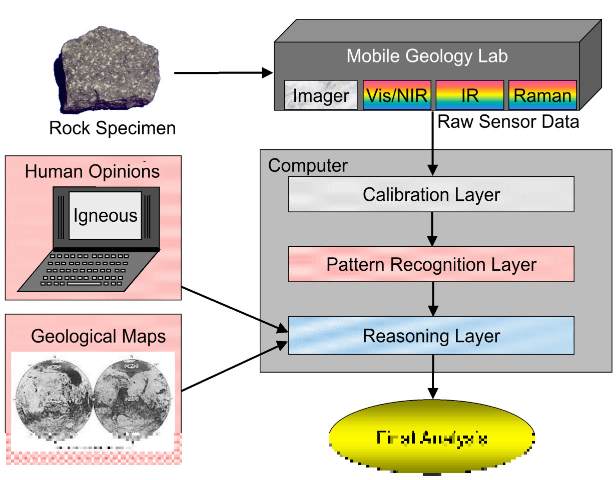
AUTOMATED ROCK IDENTIFICATION FOR FUTURE MARS EXPLORATION MISSIONS. V.C. Gulick[1], R.L. Morris[1], P. Gazis[2], J.L. Bishop[3], R. Alena[4], S.D. Hart[1], and A. Horton[1]. [1]NASA Ames/ SETI Institute, MS 239-20, [2]NASA Ames/SJSU, [3]NASA Ames/SETI Institute, MS 239-4, [4]NASA Ames, MS 269-4. All are located at NASA Ames Research Center Moffett Field, CA 94035; email: vgulick@mail.arc.nasa.gov.

Introduction: A key task for human or robotic explorers on the surface of Mars is choosing which particular rock or mineral samples should be selected for more intensive study. The usual challenges of such a task are compounded by the lack of sensory input available to a suited astronaut or the limited downlink bandwidth available to a rover. Additional challenges facing a human mission include limited surface time and the similarities in appearance of important minerals (e.g. carbonates, silicates, salts). Yet the choice of which sample to collect is critical. To address this challenge we are developing science analysis algorithms to interface with a Geologist's Field Assistant (GFA) device that will allow robotic or human remote explorers to better sense and explore their surroundings during limited surface excursions [1].

Overview: We aim for our algorithms to interpret spectral and imaging data obtained by various sensors. The algorithms, for example, will identify key minerals, rocks, and sediments from mid-IR, Raman, and visible/near-IR spectra as well as from high-resolution and microscopic images to help interpret data and to provide high-level advice to the remote explorer. A top-level system will consider multiple inputs from raw sensor data output by imagers and spectrometers (visible/near-IR, mid-IR, and Raman) as well as human opinion to identify rock and mineral samples.

Rock Analysis System Overview



Results: Our prototype image analysis system identifies some igneous rocks from texture and color information. 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. We have also developed spectral recognizers that identify high-iron pyroxenes and iron-bearing minerals using visible/near-IR spectra only. We are building a combined image and spectral database of rocks and minerals with which to continue development of our algorithms. Future plans include developing algorithms to identify key igneous, sedimentary, and some metamorphic rocks.

Some of our preliminary results from our image analysis algorithms are summarized here. In one test (Table 1), images of 16 samples of diorite and granite from diverse locations in California, Nevada, and Hawaii were used for learning. There was at least one example from each rock collection locality in the learning set. Texture and color analysis algorithms were used both separately and together to identify samples in the test set. The GFA correctly identified 9 out of 10 granite samples and 5 out of 6 diorite samples. Results were similar when using only color information from image. When using only texture, the algorithm misidentified 50% of both granite and diorites, which is not unexpected given their similar textures. This result validates the need to use a variety of inputs (texture, color, composition, etc.) to correctly identify the greatest variety of samples.

TABLE 1

Classification: Truth:	Granite	Diorite	TOTAL
Granite	9	1	10
Diorite	1	5	6

In Table 2, we used our texture algorithms to identify plutonic from volcanic igneous rocks. The algorithms were able to correctly identify plutonic rocks 88% of the time and volcanic rocks 91% of the time.

TABLE 2:

Texture ONLY				
	plutonic	volcanic	total	% correct
plutonic	22	3	25	88.00
volcanic	2	21	23	91.30

In Table 3, we used our color algorithms to identify igneous rocks of felsic, intermediate, and mafic composition.

When we applied both color and texture algorithms to both cases, we found that using texture alone for plutonic/volcanic discrimination yielded better results than using both texture and color. This would be expected since color information only complicates the discrimination problem without adding useful information. Similarly, we found that using our color algorithms alone yielded better results in discriminating between igneous rocks of felsic, intermediate, mafic composition than when combining both texture and color algorithms.

TABLE 3:

Color ONLY					
	felsic	intermed	mafic	total	% correct
felsic	5	8		13	38.46
intermed	5	20	0	25	80.00
mafic	1	7	2	10	20.00

Plans: The current preliminary tests were carried out using a limited library of rock samples as a proof of concept demonstration. Inclusion of many more samples and fine-tuning the image analysis algorithms should improve the results. In addition, we will integrate our automated spectral identification algorithms into our overall system. We will measure the spectral properties of these rock samples and test the ability of our automated spectral identification algorithms to successfully identify key mineral components in our samples. We are in the process of collecting additional representative rock samples include many more samples with which to refine our algorithm approach.

References: [1] Gulick et al. 2002, LPSC abstract.

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