AUTOMATED CLASSIFICATION OF GEOLOGICAL SAMPLES USING HIGH RESOLUTION MACRO IMAGES. P. M. Freeman[1], S.T. Ishikawa[2] and V. C. Gulick[3], [1]San Jose State University Research Foundation/NASA Ames, moriishifreeman@gmail.com; [2]EAP/NASA Ames; [3]SETI Institute/NASA Ames, virginia.c.gulick@nasa.gov; All at NASA Ames Research Center, MS 239-20, Moffett Field, CA 94035.

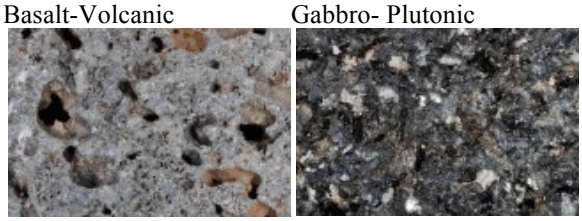
Introduction: We are developing a Geological Field Assistant (GFA) to autonomously identify geological samples using image and spectral data. In this abstract we discuss the continued effort to improve image classification algorithms using high-resolution macro images. Using higher resolution, allows our algorithms to consider fine-scale details that may be intrinsic to particular types of textures or rocks.

Methods: *Image Acquisition*: We imaged over 1025 geological samples using a Nikon D90 camera and an AF Nikkor 60mm lens to achieve 1:1 magnification. Acquired images are higher magnification and resolution than in previous work.

Texture analysis: As in previous work, we used Gabor filter decomposition for image analysis [5,7]. Since then we have expanded the size of the available data and fine-tuned our approach by validating our algorithms on a set of 57 Gabor filters generated by systematically varying parameters. We used this technique for a number of classification processes, but most effectively to classify 402 igneous rocks as either volcanic or plutonic.

FIGURE 1. Though similar in mineralogy, gabbro and basalt samples have vastly different textures

Basalt-Volcanic Gabbro- Plutonic



Machine Learning Library. We incorporated the Weka machine learning library provided by the University of Waikato into our classification scheme. In particular we used the built-in multilayer perceptron and principle components analysis [1].

Composite Image Comparison. At our closest focus, we had a very limited depth of field and so considered the use of composite images for texture analysis. For a subset of 34 samples, we produced composite images [2] from a set of 6-20 individual images. We then used our texture classification algorithms on both the composite and non-composite images and found that there was no significant improvement in classification performance using composite images. Therefore we opted to use individual images with the highest file size. Of each sample.

Color Analysis. For each image, we used mean shift color clustering to determine the dominant color modes that enable us to quantitatively describe the sample. Mean shift clustering is a non-parametric analytical tool used to identify modes in a particular feature space. Non-parametric means the technique does not specify a specific number of modes, but instead will find an arbitrary number of modes. In our case, we used the CIELUV color feature space due to its representation of perceived color as roughly corresponding to Euclidean distances. In addition to finding dominant color modes, the algorithm enables us to determine the weight for each mode as a measure of relative prevalence of that particular color in the image. To decrease the number of modes in each image, we first blurred the images and only considered modes that contributed to more than %0.5 of the pixels. We generated a color signature for each image using its modes and corresponding weights obtained from mean shift clustering [4].

We used Earth Mover's Distance (EMD) as defined in [3] to compare our color signatures. EMD is used to measure how similar two distributions are. We also normalized our signatures, in which case the EMD is a true metric. This allowed us to compare EMD between different pairs of signatures.

We used two different classification methods based on our color data, one being *k* nearest neighbor weighted voting and the other being an implementation of Weka. In this classification, we divided the data into a training set and a testing set. The training set was used to form a database of color signatures with corresponding ground truths. For each image in the testing set, we formed a texture signature and compared it to the signatures from the training set. Using EMD as a metric, we found the *k* signatures nearest to the test signature. We gave each of these *k* signatures a weighted vote, set to be inversely proportional to the EMD, in support of its ground truth. We classified the sample according to the ground truth that received the most votes. Hence, if a signature was close to signatures of a certain ground truth, it was most likely classified as the same ground truth. To ensure consistency of results, we used ten randomly selected distributions of training and testing sets with approximately 90% of the data used for training and

10% for testing in each distribution. In our experiments, we assigned *k* to be 10.

The other classification method was to create feature vectors to be analyzed by Weka's multilayer perceptron. To do this, for each sample, we made a feature vector of the EMD between the sample and every other sample in the database. We used the set of feature vectors to classify 402 igneous samples as either mafic, intermediate or felsic.

Results: *Texture Results*. Our results confirm the success of our previous experiments [5] in which we used a lower resolution camera and a smaller set of 395 igneous rocks and obtained classification rates of around 85% with less than 10% variance when classifying sample as either volcanic or plutonic. Given that 44 of 57 different tests returned percentages between 84 and 88 percent in the same classification, we have confidence that our algorithmic approach is robust. Furthermore, the 13 results outside of the 84 to 88 percent range were the 13 results with the highest frequency ranges defining the banks of Gabor filters. Hence, we have discovered an effective range of Gabor parameters that yield strong classification results and improved upon previous work with a classification rate of 86% and variance of less than 2%.

The results presented above are based on the analysis of images that we reduced to 15% of their original scale, from a resolution of 4288×2848 to 643×427. The reason for this is that it is computationally expensive to perform Gabor analysis on high-resolution images. Using 27 of the previously used 57 Gabor banks, we classified full-resolution images with accuracies ranging from 68 to 85 percent. These results are slightly disappointing, as we would expect improved classification with improved resolution. However, there are still many possibilities to explore using a higher resolution. In particular, it is unclear how Gabor parameters should be changed with changing scale and resolution, and a systematic search for effective parameters may yield better classification results.

Color Results: We used 402 igneous rocks to train and evaluate the Weka classifier's performance identifying the composition of the rocks. In one experiment, the classifier identified the rocks as felsic, intemediate, or mafic with 67.4% accuracy. Rocks were correctly identified as felsic, intermediate, and mafic with 71.7%, 57.8% and 71.6% accuracy, respectively. Using the same 402 samples, we found that the k-nearest neighbor algorithm classified samples as mafic, felsic, or intermediate with an accuracy of 70.08±9.58%. Both methods show moderate improvement over previous work in which 395 samples were classified with an overall accuracy of 63.3% and were correctly identified as felsic, mafic, and intermediate with 71.7%, 55.8% and 59.5% accuracy, respectively [5]. Notably, classification of mafic samples improved nearly 14 percentage points using the Weka method. The use of Weka for color classification is a new addition to our algorithms. Its moderate success at classification is encouraging and may be worth modest pursuit.

TABLE 1. Summary of color classification of 402 samples.

Color Results	Felsic	Inter	Mafic	% correct
Felsic	110	37	4	72.8
Intermediate	24	78	33	57.8
Mafic	12	21	83	71.6

Future Work: For much of the work presented here, we reduced images to 15% scale. Though this is a slight improvement in resolution (643×427 as opposed to 512×384) compared to previous work, in the future we plan to conduct additional experiments using higher resolution to improve classification.

Though the work presented here only considers igneous rocks, we plan to apply similar image classification techniques to sedimentary and metamorphic samples. We plan to combine this image analysis work with previous work using automated mineral classification of Raman spectra data [6] to design an automated geological field assistant.

5. References

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