

TOWARDS AUTOMATIC EXPLORATORY MINERALOGICAL MAPPING OF CRISM IMAGERY USING SUMMARY PRODUCT SIGNATURES. E. J. Allender¹ and T. F. Stepinski¹, ¹Space Informatics Lab, University of Cincinnati, Cincinnati, OH, 45221-0131, allendej@mail.uc.edu.

Introduction: Hyperspectral images taken by the Compact Reconnaissance Imaging Spectrometer for Mars (CRISM) are currently the best source of information on the mineralogy of Martian surfaces. When combined with high resolution panchromatic images and/or HiRISE-derived digital elevation models they provide the most complete information on past and present processes shaping the Martian surface. In particular, they have provided and continue to provide insight on the history of water on Mars [1]. However, working with CRISM images is challenging due to the sheer volume of data a hyperspectral image contains.

We are developing a novel method for unsupervised mineralogical mapping of CRISM imagery which can process multiple images automatically using a single processing pipeline. We envision this method as an exploratory tool which, when applied to a large collection of images, will automatically map potential locations of rare and interesting mineral deposits in each image without input from an analyst. The purpose is to comb large archives of CRISM images, inspect them for the existence of interesting deposits, flag these deposits and their 'interesting' components, and return annotated mineralogical maps of the images for manual, in-depth analysis.

To achieve this functionality we integrated two core novel technologies. First, instead of using a spectral function or a triplet of summary products as is currently standard [2], we use vectors of all popular summary products as the spectral signature of an image. This representation does not restrict which minerals can be identified while at the same time offering instant interpretation of the content of identified deposits. Second, we use the rare class discovery algorithm DEMUD [3] to identify mineralogical classes in each image. This has the advantage of identifying mineralogical "outliers," deposits that stand out from the scientifically uninteresting background.

Data: We test the feasibility of our method using 20 previously manually studied FRT images [1,4,5,6,7,8] downloaded from the PDS Mars Orbital Data Explorer. They cover a range of features including mounds, volcanoes, gullies and stratified deposits.

Method: The processing pipeline for our method has four main components: (1) image input and pre-

processing, (2) image normalization and segmentation, (3) clustering with DEMUD, and (4) mapping and validation. The pipeline is implemented in the bash environment, and calls scripts enabling functionality in ENVI IDL, GRASS, R and C throughout each processing stage.

Image input and pre-processing: Batch processing is used to complete this step for the set of images with maximum efficiency. The pipeline makes use of ENVI CAT procedures within IDL to perform photometric and atmospheric correction with artifact removal, and generate hyperspectral and multispectral summary products.

Image normalization and segmentation: Summary products are read into the R environment where they are treated as raster maps in which each pixel contained a vector of summary product values. The range of each vector component is normalized to the range between 0-1 so that the degree of similarity between summary product signatures can be assessed – in this way, whether band depth or reflectance based, each component of the signature vector contributes the same weight to the calculation. A graph-based segmentation algorithm [9] is used to (over)segment each raster in order to reduce data volume and to reduce noise through spatial smoothing. Remaining calculations are performed on resulting segments called superpixels.

Clustering with DEMUD: The superpixels are input into the rare-class detection algorithm DEMUD (with k=2 preserved eigenvectors) implemented in R. DEMUD is an iterative algorithm designed to identify a number of superpixels which are as dissimilar as possible from each other and from the rest of the superpixels. Thus, the first several iterations identify superpixels representing different interesting mineralogical deposits. In order to estimate how many mineral classes are present within an image we use the value of the reconstruction error (Rx) between the DEMUD model at a given iteration and each observation; the larger the Rx value, the more unique the mineralogical deposit identified in this iteration (Figure 1). The superpixels selected with values of Rx above a threshold are chosen as representatives of 'interesting' mineral classes within an image. This selection is one of the two elements of computational pipeline that is still performed manually in the present version of our software. The Nearest Neighbor algorithm is used to assign all superpixels (and thus the

pixels in an image) a mineralogical class on the basis of minimum Euclidean distance to representative superpixels. Superpixels too distant from all representatives are left unclassified.

Mapping and interpretation: Resultant maps of mineralogical classes are automatically produced. Along with each map, the pipeline produces a series of graphs detailing the difference between each class signature and the mean signature of the image – which is considered the 'background' signature. These graphs are used to make an interpretation of each class. This interpretation is the second element of pipeline that is currently performed manually (although it is rather straightforward); future work will automate the two manual elements of the present implementation.

Results: In the majority of the 20 surveyed images the mineralogical classes discovered automatically by our method correspond to deposits found by means of manual analysis. In some cases, such as images from [4], the striping noise was too great for meaningful classes to be discovered. In images with a lower level of noise, for example those from [5,6], our method discovered the presence of additional mineralogical classes not found using the traditional tricolor browse products.

Conclusion: Application of our method to a small survey of 20 previously manually studied FRT images

reveals that our concept of using the combination of the summary product signature representation format with the DEMUD rare-class detection algorithm works as expected and offers a feasible way to conduct larger exploratory surveys of CRISM images. Improved pre-processing and noise reduction procedures will be required for our method to be applied to a larger range of images. Algorithms for the selection of the number of classes and for their interpretation need to be implemented in order to make our method fully automatic.

Supplementary Material: The full list of 20 FRT images and the mineralogical maps produced by our method for this survey are available at <http://sil.uc.edu/pdfFiles/lpsc2014Supplement.zip>.

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