UNSUPERVISED MINERALOGICAL MAPPING FOR FAST EXPLORATION OF CRISM IMAGERY

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Introduction: Traditional mineralogical analysis of CRISM imagery is based on selecting mineral summary products [1] for sought after minerals and visualizing their spatial distributions using so-called browse products – false color images created by assigning RGB values to summary product intensities. To obtain more comprehensive knowledge about a site's mineralogical content a series of analyst-selected browse products is generated and reviewed. This process can be viewed as a *supervised* knowledge discovery – an analyst will learn only about the presence or absence of specific, a priori selected minerals. We propose here an *unsupervised* analysis of CRISM imagery – our algorithm will output a map of the site with locations of unique mineralogies (whatever they may be) marked on the map. Moreover, our method will provide information for easy a posteriori interpretation of these mineralogies. The proposed method works on actual CRISM spectra or on vectors consisting of all possible summary products. When applied to spectral data, image spectra within the range 1.0-2.6 μm (245 bands) were used as input, and when applied to summary products, vectors of 40 multi and hyperspectral products were used as input.

Method: The method consists of several steps: (1) data preprocessing, (2) image segmentation, (3) identification of mineralogically distinct classes present in the image, (4) interpretation of mineralogical classes, and (5) classification of segments and mapping. Step (2) is performed in order to reduce the dimensionality of an image by one or two orders of magnitude. Step (3) is the crucial component of our method which utilizes the DEMUD algorithm [5] for class discovery. DEMUD uses principal components modeling and reconstruction error to iteratively identify the most mineralogically distinct segments in a site. Segments are identified one by one, but, in practice, the first *k* identified segments represent *k* distinct mineralogical classes, and subsequently identified segments cycle between these classes. We identify the first 1000 most distinct segments and visualize their clustering properties using the Sammon map technique [6] in order to determine/confirm the number (*k*) of unique mineralogical classes present in the site. Spectra/vectors of summary products of the first *k* segments are the prototypes of discovered mineralogical classes. In step (4) we interpret the meaning of these classes by comparing their prototypes with a spectrum/vector of summary products corresponding the mean vector of all segments in the site – the residuals obtained from this comparison enable an estimation of each class' composition. In step (5) we classify all segments into identified classes using the nearest neighbor classifier.

Data: CRISM images frt00003e12 (Nili Fossae), frt0000ada4 (Arcadia Planitia) and frt00004af7 (Hale Crater) were obtained from the PDS Geosciences Node. These sites were selected as the mineralogy at Nili Fossae and Arcadia Planitia has been extensively studied by [2] and [3]. The mineralogy at Hale crater site has not been previously studied. Photometric and atmospheric corrections were applied using CAT software and in the case of frt0000ada4 and frt0000af7 destriping and despiking was also undertaken. Image segmentation was performed using the method described in [4]. All further processing was undertaken using GRASS GIS and R.

Results: Due to limited space in this short communication we only present the results of our mapping based on vectors of summary products. Mapping based on the spectral input yields similar results, yet classes are not as efficiently interpreted. Fig.1 shows the map of the Nili Fossae site where our method has identified four distinct mineralogies. Our interpretation of these mineralogies is shown in the legend. Our map confirms the mineralogy of the site as reported in [2], but we stress that it has been obtained automatically and without any input from an analyst except from a posteriori interpretation of the classes.

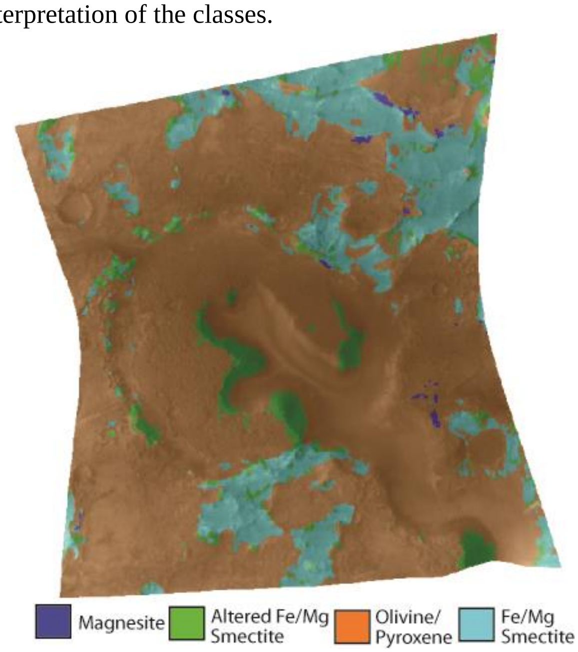

Figure 1: Map of mineral classes detected at the Nili Fossae site using a variant of our method based on vectors of summary products.

Fig.2 shows the map of the Arcadia Planitia site where our method has identified five distinct mineralogies. After our interpretation of these classes the map roughly confirms the result of mapping this site presented in [3] in which specific minerals were sought after. At this site the variant of our method based on vectors of summary products outperforms the variant based on spectral data which had difficulty distinguishing between similar spectra without the benefit of a spectral ratio.

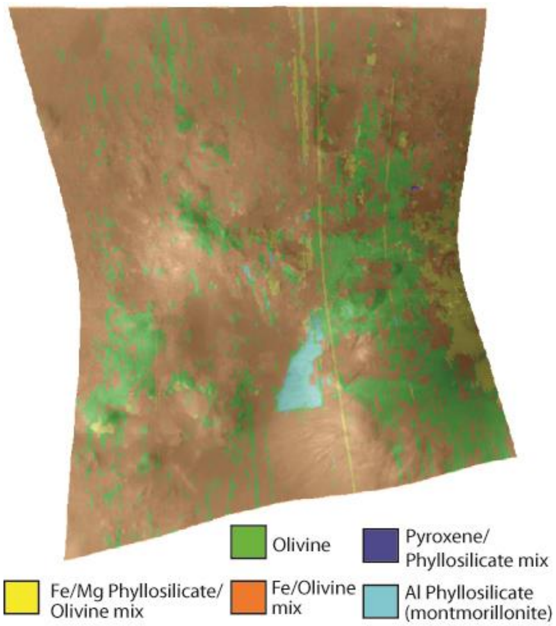

Figure 2: Map of mineral classes detected at the Arcadia Planitia site using a variant of our method based on vectors of summary products.

Fig.3 shows a map of the site at Hale crater in which our method identifies six distinct mineralogies. Gullies identified within this site were postulated to have fluvial origin [7] based on apex slopes measured using a co-registered 1m/pixel DEM derived from a coordinated HiRISE stereo image. If so, the location of the gullies should show the presence of hydrated minerals. The locations of mineralogy interpreted by us as a pyroxene/ice mix coincides with the locations of the gullies, which would also be consistent with the research of [8] who postulates that gullies may have been formed by the geothermal heating of subsurface permafrost ice, causing liquid water to flow from a shallow aquifer.

Conclusions and Future Research: Results presented here demonstrate the feasibility of our method. The method departs significantly from standard approaches of learning about the mineralogy of the Martian surface from remotely sensed hyperspectral images. It is not designed to look for a specific mineral or a class of minerals, instead it is designed to map all mineralogical classes present in a given site. This is achieved by a fully automated method, the only input from the analyst is an a posteriori interpretation of the classes, but even this is aided by the residuals between the class vector of summary products and an analogous vector calculated as the mean from all segments at the site.

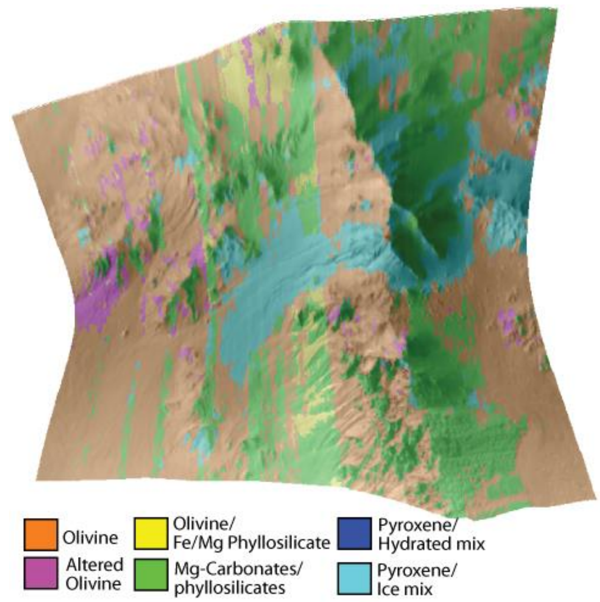

Figure 3: Map of mineral classes detected at the Hale crater site using a variant of our method based on vectors of summary products.

The method, when fully automated, would be able to survey all CRISM images in a search for interesting minerals and mineral classes, thus performing a data mining task on this resource. It could be also be applied for the creation of a global mineralogical map of Mars by utilizing the set of CRISM MRDR mosaics.

References: [1] Pelkey et al. (2007) *JGR*, *112.* [2] Ehlmann et al. (2008) *JGR*, *114.* [3] Carter et al. (2010), *Science*, *328*, 1682-1684. [4] Felzenschwalb & Huttenlocher (2004), *Int. Journal of Comp. Vision, 59(2).* [5] Wagstaff et al. (2013), *AAAI XXVII*, Paper 6171. [6] Sammon, J.W (1969), *IEEE Transactions on Computers, 18*, 401-409. [7] Kolb K.J. (2010) *Icarus*, *208(1*), 132-142. [8] Heldmann & Mellon (2004), *Icarus*, *168(2)*, 285-304.