Automatic Extraction of Unique Spectral Signatures for the M^3 database

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1. Summary

The surface of the moon consists of feldspathic and mafic minerals. The presence of mafics such as spinel, olivine, pyroxenes is helpful in understanding the crustal composition of the moon and provides clues about the mechanism of crust formation [1][2]. Identifying the unique mineral signatures present in a scene is made harder by phenomena such as intimate mixing and maturity which are pervasive on the lunar surface[3].

The sheer volume of the data from remote hyperspectral sensors outpaces the capacity for manual identification. We propose an automated algorithm that would identify these unique signatures. Various parameters have been created that are sensitive to different spectral features. We use these parameter to automate the identification of unique spectral signatures. To mitigate the effects of local instrument distortions on parameter calculation we use spline approximations of the spectra as a preprocessing step. The spectra in the image that have the clearest spectral features will have the largest parameter values. Since the number of parameters needed for identification is smaller than the number of bands in the image this also accomplishes a dimension reduction. If we consider each pixel as a point in a n-D space (n = # of parameters), and the parameter values as coordinates, the spectrally most diverse signatures will be extreme. We use simple unmixing algorithms identify these extreme points.

This processing was applied to various images from the M^3 database. The performance of the processing is compared to published expert identified signatures when available.

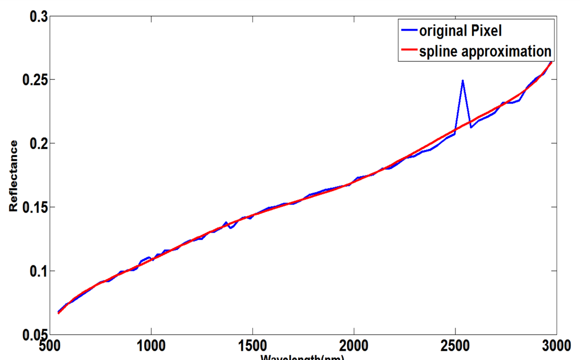
2. The Dataset

- Source: - Moon Mineralogy Mapper (M3)
- Type: - L2 reflectance data (85 usable bands) [4][5]
- wavelength range 0.43 – 3.0 µm.
- Pixel size on ground: - ~140m.

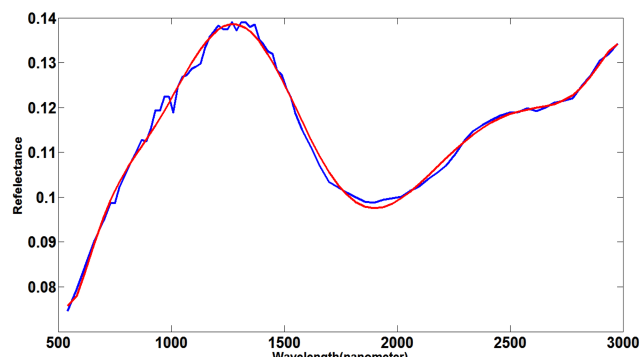
3. Mixing & Maturity

Mixing: - The Lunar surface is affected by mixing at every scale. There is intimate mixing due to the presence of microscopic mixtures on the surface and also linear mixing due to the optical integration of the signal at the detector. *Maturity*: -Due to the production of *nanophase iron (npFe⁰)* associated with space weathering spectra in lunar images are affected by (a) *reduction* in contrast of *mafic absorption bands* (b) increase in spectral slope (*reddening*) and (c) *darkening* of visible to near-infrared albedo [3]. The combination of these two processes and the presence of outliers due to local noise defeat simple linear unmixing algorithms directly applied to the data.

4. Spline Approximation



(A)Pixel with spuriously tagged as having a band at 2000



(B)Pixel with actual band at 2000

The dataset is also affected by instrument noise and distortions. Parameter calculation depends on reflectance values in certain bands and are severely affected by such distortions. To mitigate the effect of distortions, we fit all the spectra in the image with a high-penalty smoothing spline. (High Penalty splines are used to ensure that while noise is removed, important spectral information is not decimated.). In the absence of preprocessing (A) and (B) had similar values for the parameter IBD2000.

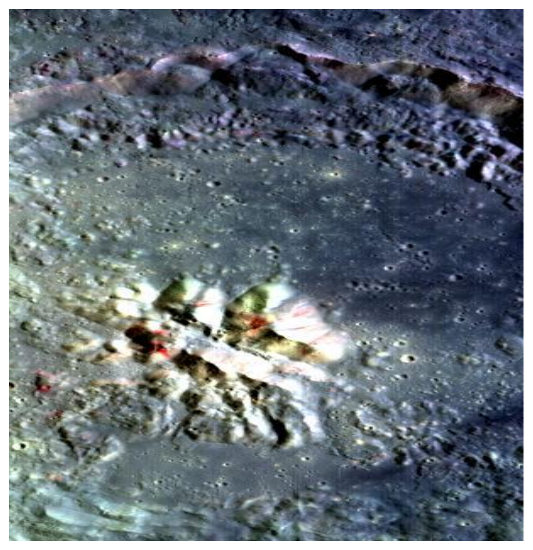
5. Parameter Maps

Parameter	Description	Identifies
IBD-1000	1µm Integrated Band Depth	Olivine and pyroxene
IBD-2000	2µm Integrated Band Depth	Pyroxene and Mg-Spinel
BD-1250	1.25 µm Band Depth	Plagioclase
BD-2300	2.3 µm Band Depth	High Ca-pyroxene
BD-1900	1.9 µm Band Depth	low Ca-pyroxene
OLINDEX		Olivine

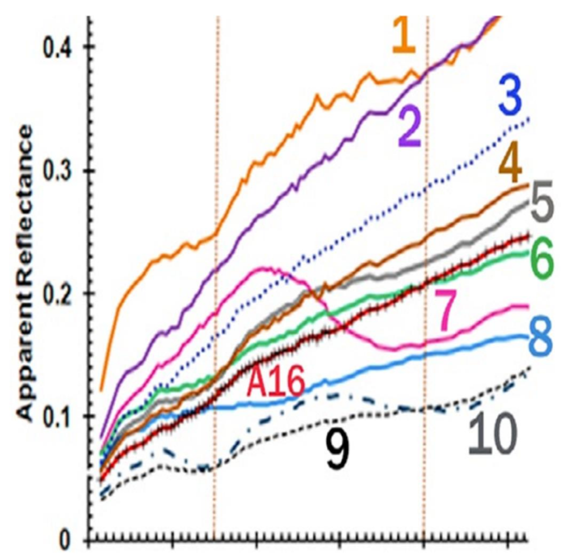
Table 1 : Parameters used in this study

Parameters have been previously used to identify the presence of spectral features of interest [1][2]. The values of these parameters scale reasonably with the 'clarity' of the spectral feature. Another useful property of the parameters is the dimensionality reduction. Each pixel can now be thought of as a point in 6D space, where the coordinates are the values of the different parameters, this can be thought of as a '***data cloud***'. The unique signatures will either have very clear features (high parameter value) or no features (low parameter value), or the extreme pixels in the datacloud. This property aids automation of unique signature identification. These extreme pixels can be found using simple unmixing algorithms such as Sequential Maximum Angle Convex Cone(SMACC) [6] or Pixel Purity Index(PPI) [7]. All the parameters in this process have been calculated as per [8].

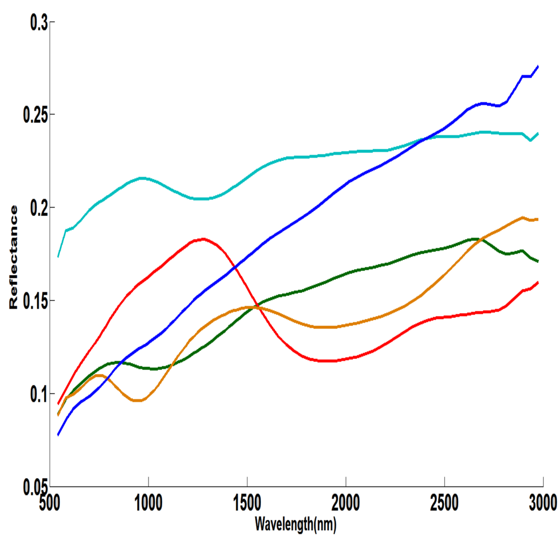
6. Unique Signature Identification In Parameter Space



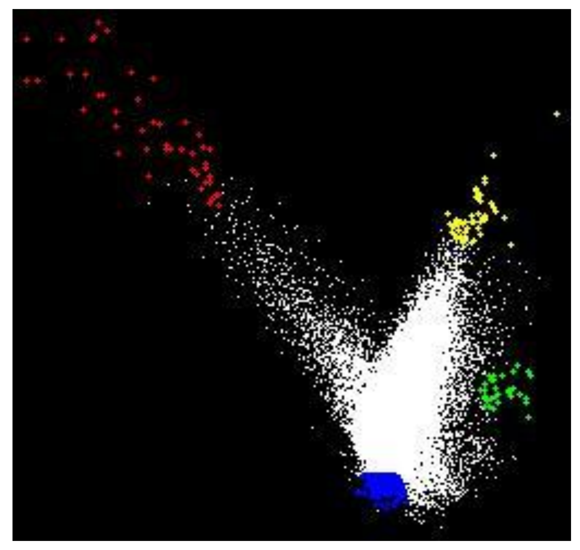
(A)RGB mosaic of the central peaks of Theophilus from the M^3 image M3G20090203T160452



(B)Signatures Identified by Dhingra et al[2].

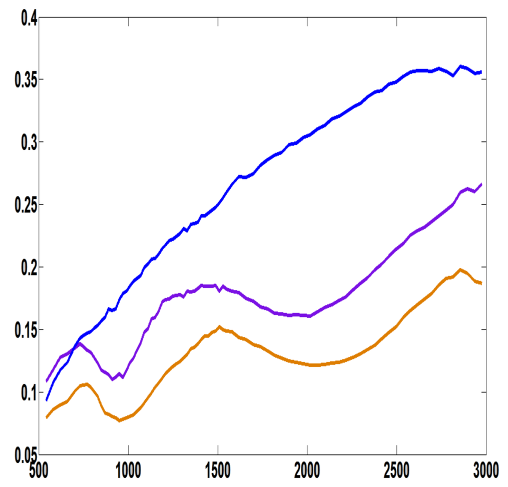


(C)End members Identified for M3G20090203T160452

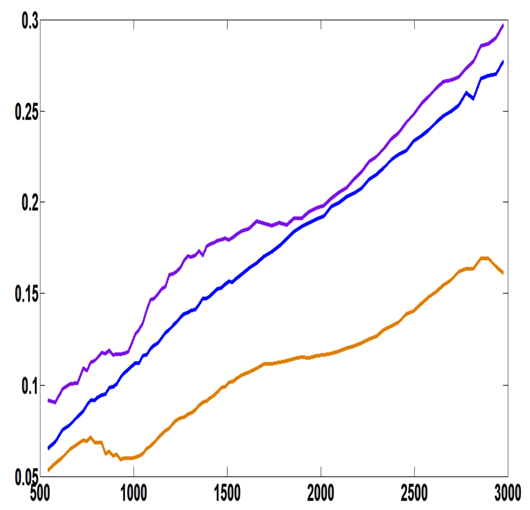


(D)Projection of Parametric Datacloud for M3G20090203T160452

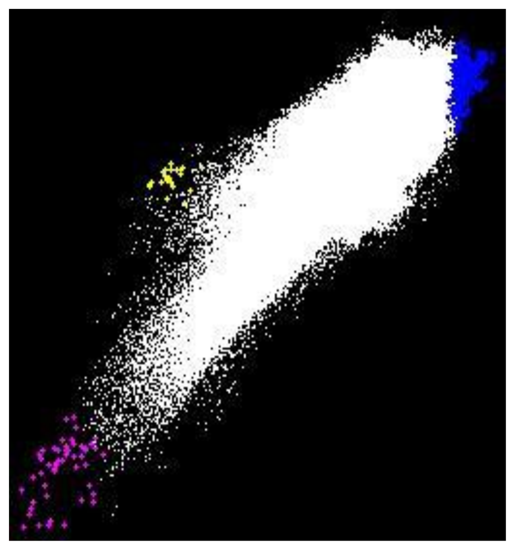
The extreme pixels in the parameter space will be those that have the largest/clearest bands. Identifying the most different pixels in this space would summarize the unique spectral signatures in the image. Extreme pixels in this space were identified by using simple linear unmixing algorithms such as Sequential Maximum Angle Convex Cone(SMACC) [6] or Pixel Purity Index(PPI) [7].The entire Theophilius Crater was studied by Dhingra et al.[2], and they identified the unique spectral signatures of interest. We processed an image strip that corresponds to the central peaks in the Theophilius crater (*M3G20090203T160452)*. Of the spectra identified by experts[2] only spectra 1, 2, 6, 7 and 8 in (B) are in the central peaks . Parameter maps were generated and the extreme points in the 'data cloud' were found. The spectra associated with pixels which were extreme is shown in (C). The results in (C) compare favorably to those spectra in (B) that are in the same region. We also show in (D) a projection of the 'data cloud in the parameter space. The Red corner corresponds to spinel while the green marks olivine, the yellow signifies pyroxenes and the blue marks plagioclases.



(E)Fresh Endmembers found in the Grimaldi Basin



(F)Mature Endmembers found in the Grimaldi Basin



(G)Projection of Parametric Datacloud- Grimaldi Basin

This algorithm was also applied to a mosaic of the Grimaldi Basin (made of many strips like the one used before). We applied a small threshold to separate out the unremarkable spectra and then find the extreme pixels in both sets. The extreme pixels and the collection of unique spectral signatures are seen in (E) and (F). A projection of the 'data cloud' is shown in (G), in this case too the endmembers map to the extreme points in the datacloud (Blue for plagioclase, yellow for low Ca-Pyroxene and Magenta for high- Ca pyroxene).

7. Future Work

Parameter maps have been successfully used to automatically identify the unique spectra in a lunar Image. But for better performance the parameter maps should account more for processes like maturity. A major advantage of these maps is that additional parameters can be added to include other features of interest

8. References

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