PRINCIPAL COMPONENTS ANALYSIS OF REFLECTANCE SPECTRA RETURNED BY THE MARS EXPLORATION ROVER OPPORTUNITY.

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Introduction: The Mars Exploration Rover Oppor- tunity has spent over six years exploring the Martian surface near its landing site at Meridiani Planum. Meridiani bedrock observed by the rover is largely characterized by sulfate-rich sandstones and hematite spherules, recording evidence of ancient aqueous environments [1]. The region is a deflationary surface, allowing hematite spherules, fragments of bedrock, and "cobbles" of foreign origin to collect loosely on the surface. These cobbles may be meteorites (e.g., Barberton, Heat Shield Rock, Santa Catarina) [2], or rock fragments of exotic composition derived from adjacent terranes or from the subsurface and delivered to Meridiani Planum as impact ejecta [3]. The cobbles provide a way to better understand Martian meteorites and the lithologic diversity of Meridiani Planum by examining the various rock types located there.

In the summer of 2007, a global dust storm on Mars effectively disabled Opportunity's Miniature Thermal Emission Spectrometer (Mini-TES), which served as the Athena Science Team's primary tool for remotely identifying rocks of interest on a tactical timescale for efficient rover planning. While efforts are ongoing to recover use of the Mini-TES, the team is currently limited to identifying rocks of interest by visual inspection of images returned from Opportunity's Panoramic Camera (Pancam). This study builds off of previous efforts to characterize cobbles at Meridiani Planum using a database of reflectance spectra extracted from Pancam 13-Filter (13F) images [3]. We analyzed the variability of rock spectra in this database and identified physical characteristics of Martian rocks that could potentially account for the observed variance. By understanding such trends, we may be able to distinguish between rock types at Meridiani Planum and regain the capability to remotely identify locally unique rocks.

Methodology: The Pancam instrument is a high-resolution, stereoscopic, panoramic camera capable of acquiring multispectral images in visible and near-infrared (VNIR) wavelengths (432-1009 nm) [4]. Our database incorporates 310 reflectance spectra of rocks and cobbles that were extracted from Pancam multispectral images [3]. Of these spectra, 70 are of bedrock and 240 are of cobbles, including the named meteorites and rocks Barberton, Heat Shield Rock, Santa Catarina, Jin, Bounce Rock, and Arkansas. Our database also contains 10 spectra of minerals that may be found on Mars, including clinopyroxene, orthopyroxene, forsterite, fayalite, hematite, magnetite, and goethite. These mineral spectra were acquired from Brown University's RELAB Spectral Database.

We defined 16 spectral parameters (Table 1) for each rock spectrum to quantitatively study differences between them, following the methods of [3, 5-8]. Each spectral parameter arises from physical characteristics that the targeted rock may exhibit, such as degree of oxidation, mineralogical composition, and albedo. We then utilized a linear form of Principal Components Analysis (PCA) to study the variance in our database of spectral parameters using the ITT Visual Information Solutions application IDL. Each component output by PCA represents a linear combination of the input variables, i.e. our spectral parameters. This allowed us to identify which physical characteristics of the targeted rocks contribute most to the overall variability of the dataset. We plotted our output components in ternary diagrams, exploring what combination of input spectral parameters and resultant components would produce plots with easily recognizable trends with the potential to differentiate between rock types. We identified which data points corresponded to bedrock, known meteorites, RELAB mineral spectra, and other cobbles to understand how different rock types plot relative to each other.

Results of PCA: When we performed PCA on all 16 parameters, we found that parameter 15 composes 89% of component 1, and accounts for approximately 88% of the overall variance in the dataset. This parameter has been used to measure the degree of oxidation of bedrock at Meridiani Planum [7], and may relate to variations in the oxidation among cobbles observed by Opportunity. However, other factors may also influence variance in parameter 15, including dust coatings [3], and concentration of hematite. Shadows do not contribute to the variance here as all spectra with shadows were excluded from our database.

We then removed parameter 15 from our dataset and performed PCA in an attempt to identify which parameters account for most of the remaining variance in the dataset. We found that parameters 9, 11, 13, 14, and 16 are the dominant constituents of the first five output components, and account for much of the remaining variability. These parameters may indicate: trends in oxidation or dust contamination (e.g. parameter 9); generic type or crystallinity of ferric minerals (e.g. parameters 9, 11, 13, 14); and albedo (e.g. parameter 16) of targeted rocks [3, 7, 8]. We also found that parameters 1-8 were negligible contributors to the variance of the dataset, and may be excluded before performing PCA with little effect on the output data.

Analysis: A plot of the first three components output by PCA when all 16 parameters are included shows that most data points plot near the vertex for component 1 (Figure 1). If parameter 15 indicates the level of oxidation of Meridiani cobbles, we would expect points nearest the vertex of component 1 to represent rocks with the greatest degree of oxidation. It is important to note, however, that parameter 15 has been used to measure the oxidation of bedrock [7]. While parameter 15 may typify the oxidation level of Meridiani cobbles, it could also represent other physical characteristics. Further research is required to fully understand the significance of parameter 15 when studying cobbles. In addition, more research is needed to better understand why outliers in Figure 1 plot away from component 1. Where available, data collected by Opportunity's Mössbauer spectrometer (MB) and Alpha Particle X-ray Spectrometer (APXS) should be used to better characterize these outliers.

When parameter 15 is excluded before performing PCA, we find that the data points spread out among the first three components (Figure 2). This reflects the absence of any single dominant component in explaining the remaining variability of the data. Note that data points representing bedrock, known meteorites, RELAB mineral spectra, and cobbles do not plot within distinct fields, which would be the ideal case for easily identifying different rock types. This makes it difficult to identify and understand potentially useful trends. Additional techniques may be needed help distinguish between different rock types. One possibility is to use the mathematical technique of Hierarchical Clustering in tandem with PCA, following the methods of [9], to better define statistically significant clusters within the dataset.

Conclusions: Much progress has been made in developing the ability to remotely identify rocks of interest at Meridiani Planum using Opportunity's Pancam. Using a database of 13F spectra of rocks and cobbles observed by Opportunity, we defined 16 spectral parameters that reflect physical characteristics of the targeted rock, and used PCA to analyze the variability in the dataset. We found that parameters 1-8 are negligible contributors to the variability of the dataset, and may be excluded. Parameter 15 dominates the variability of the dataset, and may indicate differences in the degree of oxidation among Meridiani bedrock and cobbles. Where available, data gathered by Opportunity's MB and APXS should be used to fully understand this potential trend. When parameter 15 is removed, our data points appear more widely spread, but different rock types do not plot in distinct fields. Additional mathematical techniques such as Hierarchical Clustering may be used to better define clusters within the final dataset to aid in identifying different rock types. With continued study, this methodology may be expanded upon to regain capabilities to remotely identify locally unique rocks on a tactical timescale.

References: [1] Squyres, S. W. and Knoll, A. H. (2005), EPSL, 240, 1-10. [2] Schroeder C. et al. (2008), JGR, 113, E06S22. [3] Nuding, D. L. and Cohen, B. A. (2009), LPSC XL, Abstract #2023. [4] Bell, J. F. et al. (2006), JGR, 111, E02S03. [5] Rice, M. S. et al. (2009), LPSC XL, Abstract #2134. [6] Farrand, W. H. et al. (2006), JGR, 111, E02S15. [7] Farrand, W. H. et al. (2007), JGR, 112, E06S02. [8] Farrand, W. H. et al. (2008), JGR, 113, E12S38. [9] Tréguier, E. et al. (2008), JGR, 113, E12S34.

Figure 1: Ternary diagram of first three components output by PCA including all parameters.

Figure 2: Ternary diagram of first three components output by PCA when parameter 15 is excluded. Data points spread among the three components, but different rock types do not plot in separate fields, making useful trends difficult to identify and analyze.

Table 1. Spectral parameters used in this study.