Proceedings of The National Conference
On Undergraduate Research (NCUR) 2014
University of Kentucky, Lexington, KY
April 3–5, 2014

Characterizing the Surface of Mars In the Near-Infrared

Jessica C. Snyder
Department of Physics and Astronomy
Rowan University
Glassboro, NJ 08028 USA

Faculty Advisor: Dr. David R. Klassen

Abstract

Within the Martian atmosphere today are ubiquitous dust aerosols and thin, cirrus-style water-ice clouds. To determine the water content of the clouds, using a full radiative transfer model, from spectral images of Mars, we must first understand how light is reflected from the surface. In order to do so, we begin by using principal component analysis (PCA) to search for characteristic surface spectral endmembers; the combination of these will described how light is reflected over all parts of the surface on a global scale. For this research, we used near-infrared (1.5–4.1 μm) images taken at the NASA Infrared Telescope Facility between 1994 and 1995. We chose 32 specific wavelengths where most gasses in the Martian atmosphere are not active. The images were cylindrically remapped and co-registered, then run through PCA to find the eigenvectors which characterize the surface data alone. After doing this for several sets of data, the eigenvectors were compared to check for consistency, which would indicate a characteristic model for the surface over all timescales exists. We present here today the results of these comparisons, as well as a comparison of these new results to previous median results.

Keywords: Radiative Transfer, Near-Infrared, Principal Component Analysis

1. Introduction

Studying the atmosphere of Mars from Earth requires understanding how light is absorbed in the atmosphere and relating that to the spectral data we collect. From this data, we should be able to calculate exactly how much light is absorbed at both the surface and the atmosphere. The Martian atmosphere today consists mostly of CO_2 gas but also contains significant dust and water-ice aerosols. Though the contents of the atmosphere are known, the specific amounts of each aerosol component are well characterized because disentangling the amounts of light absorbed by the surface versus the atmosphere is not a trivial task. Much research has been done to map the spectral reflectance of small, individual surface areas[1,2], but one of the major goals of our research is to model the Martian surface spectral reflectance on a global scale. By isolating the surface reflectance alone, we will be able to distinguish the amount of light absorbed in the atmosphere and, more specifically, by the water-ice aerosols in the atmosphere. From this, we will be able to complete the ultimate goal of this research, which is to measure the amount of water-ice content in the clouds over diurnal, seasonal, and inter-annual time scales. Currently, we are in the process of characterizing the surface reflectance, which this paper focuses on.

To determine how light is lost on Mars before it reaches Earth, we use a radiative transfer model (RT). Light from the Sun travels through space, enters the Martian atmosphere, reflects off the surface, travels back through the atmosphere, and then enters through Earth's atmosphere to be collected. Because basic image reduction techniques already account for the intensity of light lost in Earth's atmosphere, we ignore that component and are left with equation (1):

$$I(\lambda)=I_{sun}(\lambda)\,[1-\chi_{ice}(\lambda)-\chi_{dust}(\lambda)-(1-A(\lambda))] \quad (1)$$

where I is the measured intensity, I_{sun} is the intensity from the Sun, the χ values are the fraction of light lost due to absorption by ice and dust aerosols, and A is the surface albedo (so $1–A$ is the fraction of light absorbed by the surface). All of these parameters are functions of wavelength, λ. We have ignored the effects of the CO_2 gas in the atmosphere because we can select our wavelengths where CO_2 molecules are not active.

In the RT model, we already know $I(\lambda)$ and $I_{sun}(\lambda)$, and both ice and dust absorption physics has been adequately modeled, which leaves the surface reflectance as the missing input. If that can be modeled, then we can adjust the amounts of ice and dust until the model intensity matches the actual measured intensity, and thus we can recover the total amount of water ice in the clouds.

2. Data

Our research group has extensive near-infrared spectral image sets taken during every opposition from 1995 through 2003 (roughly every 25 months). These images were taken at the NASA Infrared Telescope Facility on Mauna Kea, Hawaii using the NSFCAM. We made use of its circular variable filter (CVF) in order to choose a specific set of 32 wavelengths between 1.5 and 4.1 µm. The spectral resolution ($\Delta\lambda/\lambda$) of the CVF is about 1%. For this work we focused on data sets taken in the 1994–1995 opposition. See Table 1 for details.

Table 1. data set details

Date	Set #	UT Time Range	Size (arcsec)	Season
28 DEC 1994	2	12:57–13:18	10.8	Late N spring
	3	14:17–14:38		
14 JAN 1995	1	11:56–12:17	12.3	N spring–summer
	2	14:09–14:32		

3. Analysis Methodology

To determine how much light is lost at any part of the surface, we need to find an acurate spectral model for $A(\lambda)$ that describes surface reflectance based on the data we collect. The basic idea is that we can break down the spectral reflectance of any part of the surface into a linear combination of "pure" spectral endmembers. The simplest such model would be to call the brightest and darkest regions our endmembers, then everywhere else is just a linear mixture of those two[3]. However, such simple models assume that regions in the data actually are sufficiently spectrally pure they can act as an endmember. Previous work shows that they are not[4].

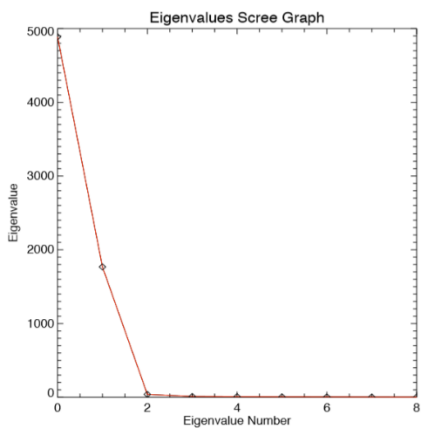
To create a characteristic model from the spectral data, we need a technique that will isolate the surface spectral signatures from the atmospheric spectral signatures. The technique we chose was principal component analysis (PCA). PCA can be defined as "primarily a data-analytic technique that obtains linear transformations of a group of correlated variables such that certain optimal conditions are achieved. The most important of these conditions is that the transformed variables are uncorrelated"[5]. Essentially, we are looking for those unique "variables" through our spectral data sets that best characterize the data—we move from a data space defined by the wavelengths of light observed to a space defined by "traits" of Mars that characterize the maximum variance within the images. Mathematically, these new variables are eigenvectors of the data variance/covariance matrix.

Conceptually, all our data can be thought of as points in a 32-dimensional space (the wavelengths used) and we are looking for the longest directions through the data cloud. Table 2 summarizes how PCA works for Martian surface spectra. Based on previous research[4], we have found that the first three or four eigenvectors can account for over 99% of the data variance. Figure 1 shows a graph of the eigenvalues for the first nine eigenvectors. In PCA, the

eigenvalues are a direct measure of the amount of variance contained in that dimension. This means that not only do we have a data space where the dimensions are based on the intrinsic data variance, but we have also effectively reduced the size of that space from 32 dimensions to 3–4. And since each eigenvector is based in intrinsic data characteristics, each one can be ascribed to a trait of the data, as we will show in the next section.

Table 2. how PCA works for Martian surface spectra

Visually	Analytically
• Plot all spectral data into 32-space • Find paths through data with maximal amount of variance	• Compare brightness measurements of different regions at different wavelengths • Calculate variances and co-variances between measurements and put into a 32x32 matrix • Find 32 eigenvalues and eigenvectors (i.e. surface characteristics and spectral data paths) • Analyze for significant eigenvectors



Num	Eval	%Var
0	4888.25	72.6560
1	1767.70	26.2740
2	38.7039	0.575271
3	10.4602	0.155475
4	7.41814	0.110259
5	5.78977	0.0860557
6	4.43665	0.0659437
7	3.16516	0.0470450
8	2.01336	0.0299254

Figure 1. Scree graph of surface spectra eigenvalues

This technique for finding surface spectral models will be especially useful if the pure surface endmembers are constant—previous work[4] leads us to believe this may be true, and we will check the significant eigenvectors from this work to those for overall consistency.

To begin extracting the eigenvectors from the data sets, all of the images in each set must be cylindrically remapped and registered. The spectra from each image can then be run through PCA (in a program written in IDL). In the program, we plot the average spectral reflectance of six different regions on the surface image to help us identify the eigenvector traits in the data. Then we plot the first four eigenvectors for each data set. Finally, these eigenvectors are compared across data sets, as well as to previous median results, to check for consistency over time.

4. Results

Figures 2.1–2.4 show the PCA of our four data sets. In each figure there is a continuum image of Mars (cylindrically remapped) with six regions of interest highlighted, a PCA plot of the spectral data in the 1st eigenfunction versus the 0th eigenfunction space, with the points from the same six regions highlighted, and a graph of the average spectrum of the six regions. Within the highlighted regions are four major vertices in PCA space: red for bright regions, yellow for dark regions, green for the polar region, and cyan for the shade regions. As can be seen, the reason these regions are interesting is that they tend to lie at, or near, vertices of the PCA data cloud—they represent eigenvector trait endpoints and are thus possible candidates to guide the recovery of spectral endmembers.

The blue and purple regions also represent interesting, near-vertex points, but are usually not endpoints. Each colored line on the average spectra plot corresponds to a matching color in the PCA plot and region on Mars and shows clearly that the brighter regions (red or green) have higher average reflectance over each wavelength compared to darker regions (yellow or cyan). Because the brightest and darkest regions bound the 0th eigenvector, we interpret this trait to be an overall, general albedo. Because the coldest, ice-covered, regions and the warmest regions bound the 1st eigenvector, we interpret this trait to be temperature/iciness. By similar analysis, the other two eigenvectors appear to be correlated with large-scale and smaller-scale geology.[4]

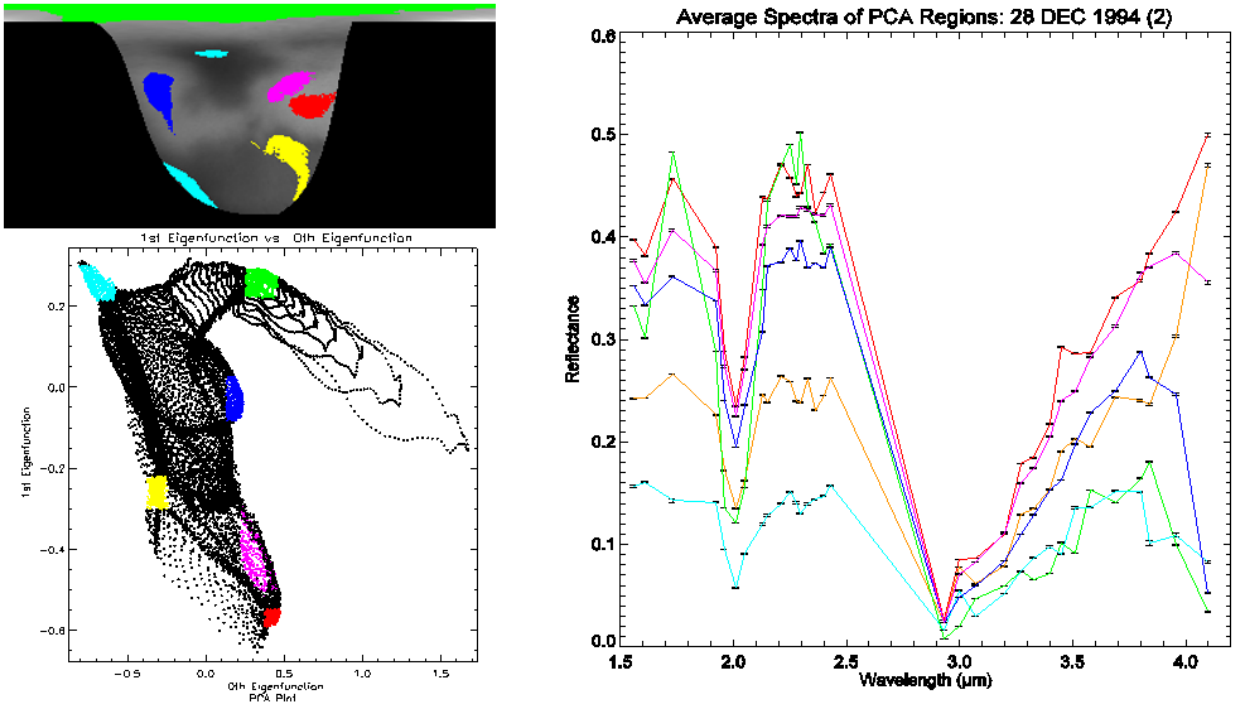


Figure 2.1. Surface image, PCA plot and average spectra plot for Dec. 28, 1994, Set 2

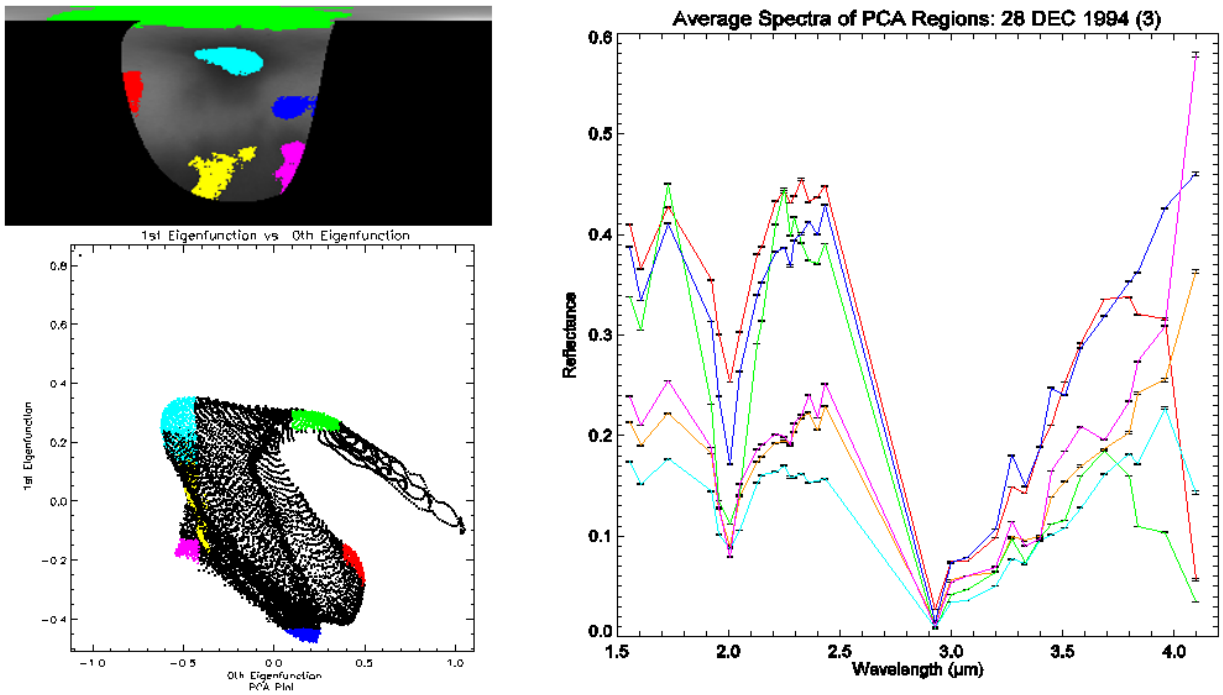


Figure 2.2. Surface image, PCA plot and average spectra plot for Dec. 28, 1994, Set 3

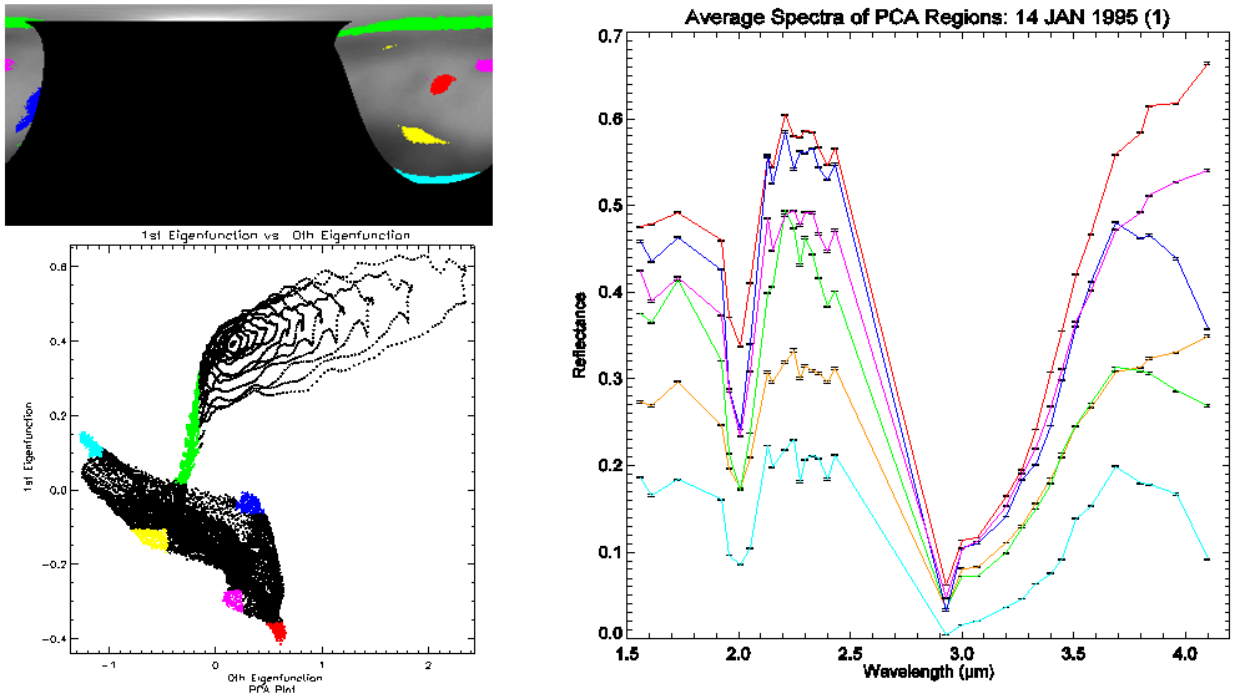


Figure 2.3. Surface image, PCA plot and average spectra plot for Jan. 14, 1995, Set 1

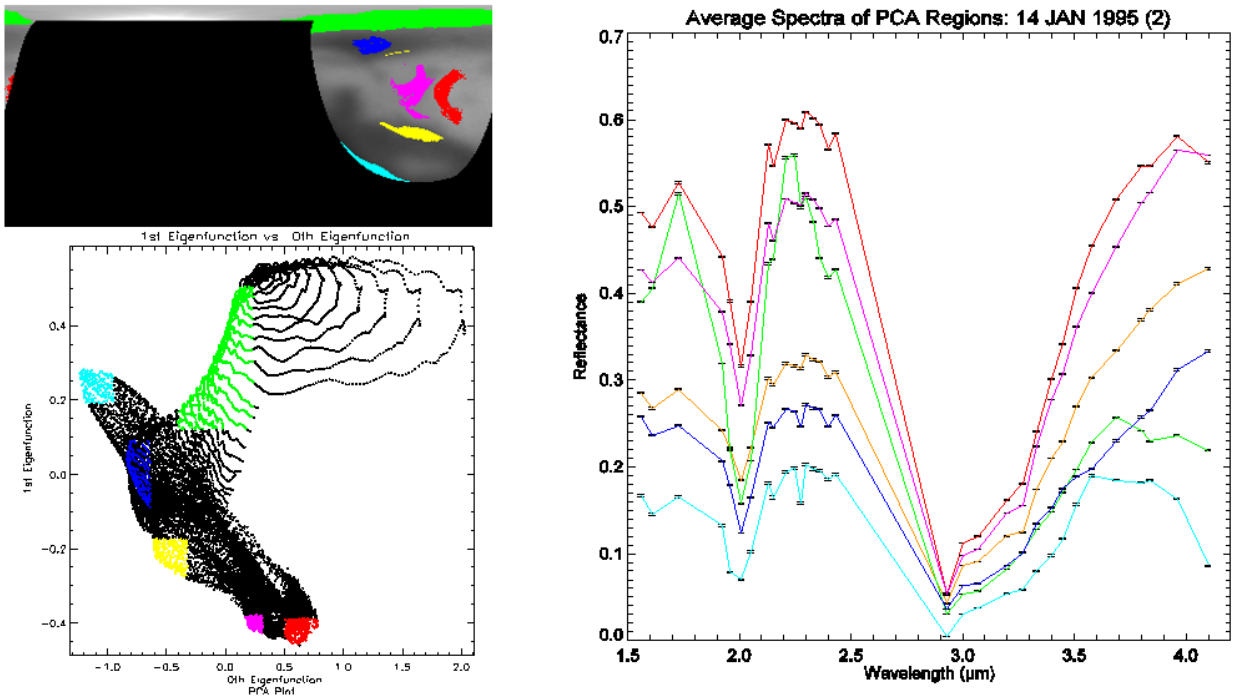


Figure 2.4. Surface image, PCA plot and average spectra plot for Jan. 14, 1995, Set 2

We also used our program to find and plot the first four eigenvectors for each data set. In Figures 3.1 through 3.4 we have the plots for eigenvectors 0, 1, 2 and 3, respectively. It can been seen that the first three eigenvectors for each data set follow a relatively similar spectral shape, and a shape similar to the median eigenvector from previous work. This bolsters the consistency idea. However, for eigenvector 3, the spectra are very scattered and uncorrelated, meaning that eigenvector 3 is either characteristic of data noise, or perhaps some very localized geology—since we see different regions within our entire field of view for each data set, differing geologic regions come into, and go out of, view. We would not expect a trait based on localized geology to be entirely consistent over all data sets. Of course, this dimension is also relatively insignificant, as we see from its eigenvalue in Figure 1, so its contribution to potential endmembers will also be small.

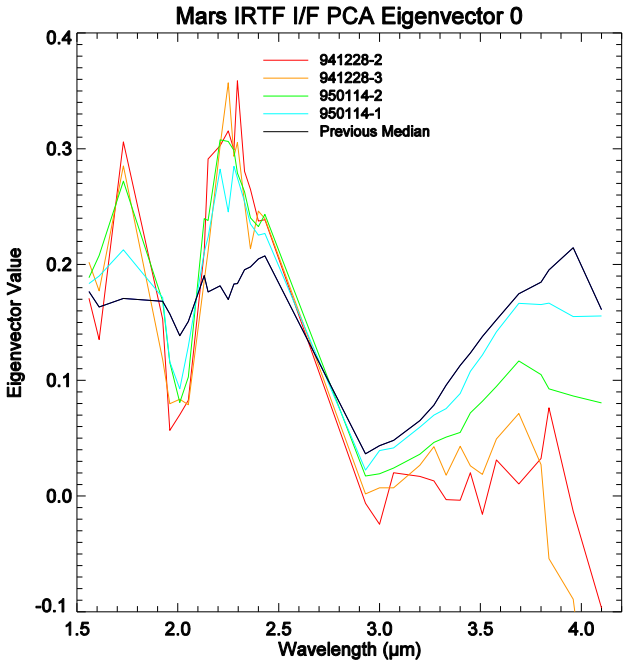


Figure 3.1. Eigenvector 0 plot

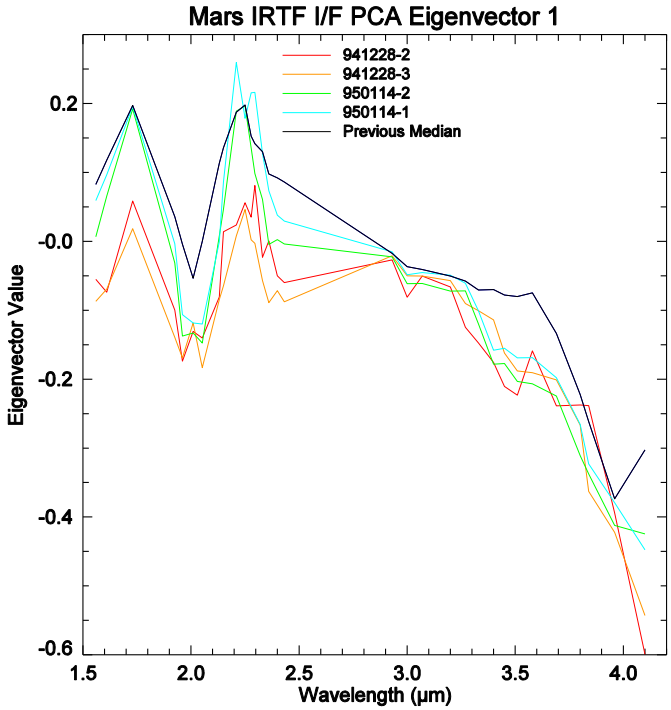


Figure 3.2. Eigenvector 1 plot

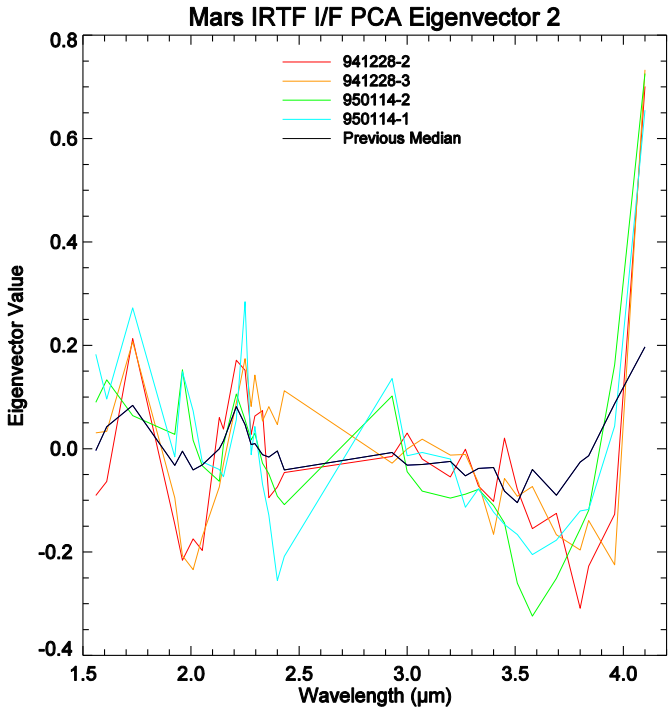


Figure 3.3. Eigenvector 2 plot

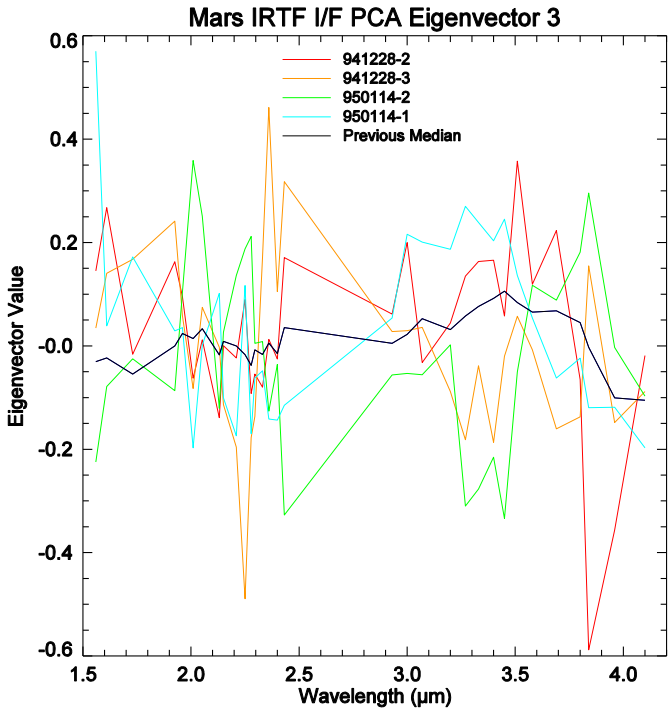


Figure 3.4. Eigenvector 3 plot

5. Conclusions

Based on our results, we conclude that these spectral data are producing spectral shapes that show relative consistency over time, meaning we should be able to create a single set of characteristic model endmembers for the surface reflectance; however, more data sets will need to be run through PCA and analyzed to further confirm the consistency of the surface reflectance over time. The first three eigenvectors account for almost 99% of all the spectral data and will be used primarily to construct our final model. Future work will be carrying out this next step of combining the eigenvectors to create the surface spectral endmembers which can then be used in the RT modeling to finally recover the ice cloud optical depth and thus the water content in the clouds.

6. Acknowledgments

This work has been supported by NASA Mars Data Analysis Program (NAG5-11076) and by both the National Science Foundation Planetary Astronomy and Research at Undergraduate Institutions programs (0307924 and 1008744).

7. References

1. Mangold, N., Gendrin, A., Gondet, B., Lemouelic, S., Quantin, C., Ansan, V., Bibring, J.-P., Langevin, Y., Masson, P., Neukum, G. (2008), Spectral and geological study of the sulfate-rich region of West Candor Chasma, Mars, *Icarus*, *194*, 519–543.

2. Mustard, J. F., Murchie, S. L., Pelkey, S. M., Ehlmann, B. L., Milliken, R. E., Grant, J. A., Bibring, J.-P., Poulet, F., Bishop, J., Dobrea, E. N., Roach, L., Seelos, F., Arvidson, R. E., Wiseman, S., Green, R., Hash, C., Humm, D., Malaret, E., McGovern, J. A., Seelos, K., Clancy, T., Clark, R., Marais, D. D., Izenberg, N., Knudson, A., Langevin, Y., Martin, T., McGuire, P., Morris, R., Robinson, M., Roush, T., Smith, M., Swayze, G., Taylor, H., Titus, T., Wolff, M. (2008), Hydrated silicate minerals on Mars observed by the Mars Reconnaissance Orbiter CRISM instrument, *Nature*, *454*, 305–309.

3. Singer, R. B., McCord, T. B. (1979), Mars: Large scale mixing of bright and dark surface materials and implications for analysis of spectral reflectance, In: Lunar and Planetary Science Conference, Volume 10, pp. 1835–1848.

4. Klassen, D. R. (2009), Principal components analysis of Mars in the near-infrared, *Icarus*, *204*, 32–47.

5. Jackson, J. E. (2004) Bibliography, A User's Guide to Principal Components, John Wiley & Sons, Inc.,