BAND SELECTION METHOD APPLIED TO MOON MINERALOGY MAPPER (M^3). P. D. Cavanagh[1] and L. Li[2], [1]Department of Electrical and Computer Engineering, Indiana University-Purdue University Indianapolis, 723 W. Michigan Street, Indianapolis, IN 46202 (pdcavana@iupui.edu), [2]Department of Earth Sciences, Indiana University-Purdue University Indianapolis (ll3@iupui.edu).

Introduction: As technology continues to advance, remote sensing optical sensors, such as those onboard weather satellites and planetary probes, are able to detect and measure solar radiation at both improved spectral and spatial resolution. In particular, a hyperspectral dataset often consists of tens to hundreds of specified wavelength bands. One drawback of large spectral datasets is information redundancy resulting from high correlation between narrow spectral bands. Reducing the data dimensionality is critical in practical hyperspectral remote sensing applications. Fewer spectral bands can aid in both spectral modeling and optical sensor design.

Due to the large size of hyperspectral datasets, computation time incurred through spectral modeling methods is often prohibitive. By decreasing the data dimensionality, the datasets can be more efficiently input into models, such as partial least squares regression (PLS) and radiative transfer modeling, in order to reproduce reflectance spectra and estimate mineral abundances of planetary surfaces.

Once an optimal subset of a hyperspectral dataset is known, the selected bands can then be used to inform future optical sensor design. The decreased number of bands needed to image a chosen location can decrease both cost and the amount of data being recorded. If the sensor is investigating a location at which no prior information is known, the band selection algorithm could be embedded into the flight software in order to reduce the size of information being transmitted, effectively ignoring the unneeded information.

Previous studies by Price [1-3] have introduced a band selection method which can be used to accurately reconstruct a hyperspectral dataset with a limited number of bands. The research presented examines the feasibility of Price's method for extracting an optimal band subset from recently acquired lunar hyperspectral images recorded by the Moon Mineralogy Mapper (M^3) on board the Chandrayaan-1 spacecraft.

Background: Decreasing data dimensionality is a vast area of research that has been applied to hyperspectral remote sensing as the spectral and spatial resolution of modern sensors has increased. Originally proposed by Hughes [4], the curse of dimensionality describes how an increase in resolution is not always beneficial when analyzing a hyperspectral scene. Linear transformation, such as principle component analysis (PCA) has often been used to reduce the dimensionality of hyperspectral datasets [5]. Although effective, PCA requires a large amount of computation in order to complete the inversion of large hyperspectral datasets. Therefore, preliminary methods of band selection are required to decrease the dataset prior to PCA. Recently, a genetic algorithm combined with selective PCA was used for feature extraction with encouraging results, but the algorithm requires the use of ground data [6]. The algorithm could be applied to areas of the lunar surface where samples are available; however, it would not be applicable to previously unexplored sites. A recent report of various band selection methods [7] referenced Price's method as particularly relevant to sensor design. Additionally, the M^3 instrument is similar in design and performance to the AVIRIS instrument, which Price used to conduct his band selection experiments.

Methods: Price's band selection method was used to perform the hyperspectral reconstruction with the M^3 dataset acquired from the Chandrayaan-1 spacecraft. The Apollo 17 landing site was chosen to test the algorithm.

Price's Band Selection. Price's band selection of hyperspectral data was implemented using MATLAB. The method is composed of two main phases that occur iteratively:

1) The method performs a Gram-Schmidt procedure to create a set of basis functions that represent a rough approximation of a specified hyperspectral data set. After the Gram-Schmidt vectors are determined, principal component analysis (PCA) is performed and eigenvectors representing the variability of the dataset are computed. By analyzing the first eigenvector, which represents the greatest variability of the dataset, a wavelength band is selected that covers the portion of the eigenvector with the greatest value.

2) Once the width of the band is determined, a basis function and wavelength integral can be established in order to approximate the dataset.

After each iteration, the reconstructed approximations are summed and compared with the original dataset. When the error is very small ($R(M) < 0.01\%$), the process is completed.

M^3 Data and Apollo 17 Landing Site. The Apollo 17 landing site was chosen to test the band selection algorithm due to its diverse geological features. The landing site is located in the Taurus-Littrow Valley and is comprised of both bright feldspathic highlands and

dark basalt rich mare. The M^3 data from the landing site was radiometrically calibrated into reflectance values. The result of the calibration was a hyperspectral dataset consisting of 74 bands ranging from 0.461 to 2.537 µm. The total size of the landing site evaluated was 100 x 100 pixels.

Statistical Analysis. In order to verify the results, multiple methods for error analysis were employed. The initial error threshold was originally presented by Price [8] and is defined as

$$R(M) = 100\% \left\langle \int \left(\mathbf{x} - \sum_{i=1}^{M} S_i \varphi_i \right)^2 \mathrm{d}\lambda \right\rangle \Big/ \left\langle \int (\mathbf{x}^2) \mathrm{d}\lambda \right\rangle$$

where $\mathbf{x}$ is defined as the original dataset and $\sum S_i \varphi_i$ is defined as the sum of weighted basis functions representing the reconstruction of the original dataset. Additionally, the error of the reconstruction was analyzed using the RMS error of the difference between the original and reconstructed datasets.

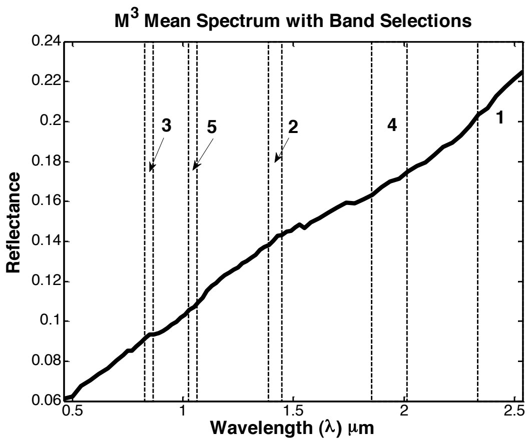

Figure 1. Band selections used for reconstruction.

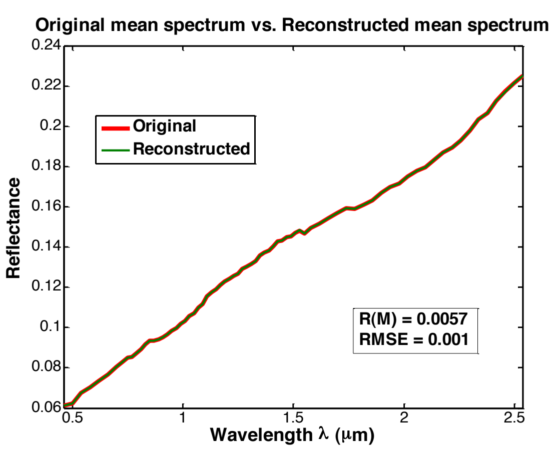

Figure 2. Original vs. reconstructed mean spectra.

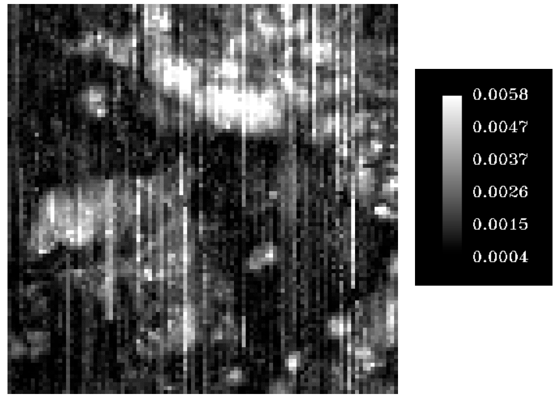

Figure 3. RMSE Image of Apollo 17 Landing Site.

Results: The band selection method identified 15 bands of the original hyperspectral dataset for the Apollo 17 landing site, which can be used to reconstruct the 74 original bands with minimal error (<0.01%). This indicates an accurate reconstruction using only 20% of the original dataset. The 15 channels selected are located in five spectral intervals presented in Fig. 1 and were used to reconstruct the dataset with R(M)=0.0057% and a RMSE=0.001% (Fig. 2). The RMSE image (Fig. 3) features both noise and some resemblance of the geologic features.

Conclusions: The results of this study show that by using 20% of the original hyperspectral dataset, the 74 bands of the Apollo 17 landing site can be reproduced. The band selection results can help to configure spectral channels of future optical instruments for lunar and planetary exploration. In particular, optical sensor channels can be chosen based on the knowledge of which wavelength bands represent the greatest relevant information for characterizing geology of a particular location. Future work will refine the band selection method to incorporate a noniterative approach. Additionally, the procedure will be applied to other hyperspectral datasets such as the LSCC dataset. We will perform PLS on the resulting datasets to determine mineral abundance and then compare with the analysis from the full hyperspectral dataset.

References: [1] Price J. C. (1975) *JGR*, 80, 1930-1936. [2] Price J. C. (1990) *Remote Sensing Environ., 33,* 113-121. [3] Price J. C. (1992) *Int. J. Remote Sensing, 13,* 2593-2610. [4] Hughes G. F. (1968) *IEEE Trans. On Inform. Theory, 14,* 55-63. [5] Harsanyi J. C. and Chang C. I. (1994) *IEEE Trans. on Geosci. & Remote Sensing, 32(4),* 779-785. [6] Yao H. B. and Tian L. (2003) *IEEE Trans. on Geosci. & Remote Sensing, 41(6),* 1469-1478. [7] Bajcsy P. and Groves P. (2004) *Photogrammetric Engr. and Remote Sensing, 70(7),* 793-802. [8] Price J. C. (1994) *Applied Optics, 15,* 3281-3288.