MINERAL MAPPING FROM CHANG'E 1 DATA

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ABSTRACT

This paper presents a detailed application of two recently developed methodologies for non-linear unmixing, applied to the Inference Imaging Spectrometer (IIM) sensor on board of the Chinese Chang'E-1 mission. In the framework of the Moon Mapping project, jointly sponsored by the Italian Space Agency and the Center of Space Exploration (COSE) of the P.R. China, a p-linear mixing (p-LMM) model has been applied to data by the first Chinese exploration mission to the Moon. The rationale for using non-linear unmixing models is the intimate mixture characterizing the materials on the Moon surface, and the multi-path and multi-reflection phenomena occurring on its rugged surface, especially at the rather coarse spatial resolution (200 m) of the IIM sensor. Two test areas have been considered, namely the landing site of the Apollo 17 mission, where additional information from US probes is available, and a second - much wider - area, selected by COSE as one of the possible landing sites for future Moon operations. Mineral map extractions using p-LMM have been considered and compared with those obtained by means of the modified partial least squares regression (PLSR) methodology. Results show that the proposed approach is able to obtain results consistent with those obtained by the previous works without requesting a priori knowledge of the chemical composition of the Moon surface, just the spectra of the materials to be considered.

KEYWORDS

Moon mineralogy, nonlinear unmixing, polytope decomposition, spectral analysis, mineral composition

INTRODUCTION

Earth and planetary surface observations have taken strong advantage of recent developments in remote sensing technology [1]. In fact, the characterization of the structure of the considered targets benefits from the complex spectral investigations allowed by high spectral resolution in the records acquired by probes and sensors. This feature is especially interesting for planetary research and exploration [2] [3], since the efforts to recover ground data and samples from extraterrestrial bodies are extremely large. Therefore, reliable investigation on surface composition by means of records remotely acquired by spectrometers can improve the characterization of the surface without requiring to actually reach that surface [4] [3].

Among extraterrestrial bodies, the Moon is a very interesting example for many reasons. Its interest is also high from a geophysical point of view. Indeed, Moon is a differentiated planet such as Earth [5] [6] [7]. Its crust results from the deposit and evolution of magmatic lithologies which include mafic minerals (i.e., minerals enriched in iron and magnesium, such as olivine, orthopyroxene and clinopyroxene). The geological mechanisms that formed the materials at the surface and near-surface through various mantle processes and crystallization conditions can be reconstructed from the knowledge of the specific mineral assemblages and their major element chemistry. Moreover, its planetary thermal and chemical evolution is a powerful evidence for unraveling the Moon geologic history, and it, too, can be described by exploring the composition and mineralogy of the surface [8].

Typically, the Moon surface has been characterized by investigation based on modal and chemical research of surface rocks. Accordingly, a reliable estimate of the abundances of each mineral in an area can be retrieved by using adequate deconvolution techniques, such as those based on modified Gaussian model (MGM) and partial least squares regression (PLSR) [7] [9] [10]. The outcomes of these techniques might reach high accuracy. However, they usually have a large computational cost, especially when large-scale datasets are considered.

As an alternative, spectral unmixing methods can provide a remarkable enhancement with respect to computational costs [1] [11] [12] [13]. Spectral unmixing separates the target pixel spectrum into a set of constituent spectral signatures (endmembers) combined by means of a set of fractional abundances. In particular, our bet is that a more accurate characterization of the surface may be achieved by means of higher order nonlinear spectral unmixing. In fact, it has been demonstrated [11] [12] [13] [1] [14] that these algorithms are able to effectively describe spectrally and geometrically complex scenarios.

In this paper, we aim at using higher order nonlinear HSU methods to achieve accurate characterization of the mineralogical composition of the Moon surface. To this aim, we exploit higher order mixture models to efficiently obtain a reliable distribution of the minerals' abundances. We use the retrieved coefficients driving the spectral mixtures to estimate the minerals in the areas corresponding to each of the pixels of four test areas. Experimental results on these areas are finally validated by comparison with with the outcomes of the above mentioned and well established PLSR method, so that it is possible to appreciate that non-linear spectral unmixinh is actually able to provide significant information about Moon surface composition.

METHODS

It has been proved that unmixing techniques are able to provide accurate description of the materials in the local instantaneous field-of-view by characterizing the interactions among the basic materials in the area [11] [14] [13] [12]. Moreover, since the inversion process carried out over the mixture models depends only on the endmember spectra, spectral unmixing methods are not sensitive on statistical distribution parameters. As absorption characteristics vary nonlinearly according to the abundance distribution, nonlinear spectral unmixing methods are appropriate for understanding and quantifying the physical-chemical composition of the materials on the Moon surface.

Higher order nonlinear mixture models can indeed help in describing extraterrestrial surfaces, strongly depending on intimate mixture features, such as grain size and illumination angles [1] [5] [3] [7] [12].

They can be generally written according to the following expression:

$$\underline{y}_l = \sum_{k=1}^{p} \sum_{r=1}^{R} \omega_{rkl} \psi_k(\underline{m}_r) \qquad (1)$$

where $\underline{y}_l = \left[y_{l_n} \right]_{=1,\ldots N}$, $y_{l_n} \in \Re$ is the N-band spectral signature of the l-th pixel, R is the number of endmembers, and $\underline{m}_r = \left[m_{r_n} \right]_{=1,\ldots N}$ is the the N-band spectral signature of the r-th endmember, being $r \in \{1,\ldots, R\}$. Further, $\psi_k(\circ)$ represents a k-th order nonlinear function of the given endmember spectrum. Hence, when $\psi_k(\underline{m}_r) = \underline{m}_r^k$ (where $\underline{m}_r^k = \left[m_{r_n}^k \right]_{=1,\ldots N}$), the aforesaid equation identifies the p-linear mixture model (pLMM) [11].

The goal of nonlinear spectral unmixing is to evaluate each ω term, in order to understand the nature of the endmember combination that delivers the given target observation spectral signature.

We proved in [11] that the coefficients driving the nonlinear combination in (1) can be obtained by means of a linear system involving the original hyperspectral data and the endmembers' spectra delivered by an endmember extraction algorithm (EEA, and exploiting polytope decomposition (POD) can be used to retrieve the ω coefficients.

Once the linear and nonlinear coefficients are retrieved, a proper combination of them can provide a more accurate estimation of the endmember abundances. In order to compute them, we proposed [11] a global metric based on the polytope representation. Indeed, given ω_l as extracted according to the overdetermined linear programming optimization, the spectral representation of the reconstructed pixel $\hat{\underline{y}}_l$ can be represented as:

$$\hat{\underline{y}}_{l_n} = \sum_{r=1}^{R} \varphi_{rl_n} \psi_1(m_{r_n}) = \sum_{k=1}^{p} \sum_{r=1}^{R} \omega_{krl} \psi_k(m_{r_n}) \qquad (2)$$

where φ_{rl_n} is the overall contribution of the r-th endmember to the reconstruction of the l-th pixel over the n-th band. Hence, it is possible to think to φ_{rl_n} as the compression/expansion factor of the r-th endmember over the n-th direction in the N-dimensional space. As the relevance of the r-th endmember in contributing to the reconstruction of the l-th pixel increases, the amplitude of $\underline{\varphi}_{rl} = \left[\varphi_{rl_n}\right]_{n=1,\ldots N}$ gets larger as well.

In order to quantify the contribution of each endmember to the reconstruction of the l-th pixel, let us consider the polytope that is induced by the vertices identified by $\underline{\varphi}_{rl}$. Given our assumptions such a polytope is a simplex [3]. Therefore, we can define its volume as $V_{\underline{\varphi}_{rl}} = \frac{1}{N!} \det\left[\Delta(\underline{\varphi}_{rl})\right] = \frac{1}{N!} \prod_{n=1}^{N} \varphi_{rl_n}$, where $\Delta(\underline{\varphi}_{rl}) = \left[\delta_{ij}(\underline{\varphi}_{rl})\right]_{(i,j)\in\{1,\ldots N\}^2}$ is the diagonal matrix induced by the $\underline{\varphi}_{rl}$ spectral signature [11] [14] [12]. Hence, $V_{\underline{\varphi}_{rl}}$ can be used to determine a valid and reliable characterization of r-th endmember aggregate abundance, as it involves all the spectral interactions provided by the aforesaid endmember.

Thus, the r-th endmember abundance $\hat{a}_{rl}$ can be defined as:

$$\hat{a}_{rl} = \frac{V_{\underline{\varphi}_{rl}}}{\sum_{i=1}^{R} V_{\underline{\varphi}_{rl}}} \qquad (3)$$

The abundance estimates $\hat{a}_{rl}$ fulfill the sum-to-one and the non-negativity constraints [1]. Furthermore, it is possible to consider $\hat{a}_{rl}$ as an aggregate metric to estimate the abundance of the r-th endmember in a pixel, where the contributions of each order is weighted by the endmember itself. This results in a more stable and reliable metric in order to get an evaluation of the presence of each endmember in the scene [11] [14].

As previously mentioned, acquiring univocal and well defined spectral signatures of minerals over extraterrestrial bodies' surface can be cumbersome. Indeed, geomorphological and geophysical properties as well as illumination conditions can strongly affect the signals that are remotely sensed by spectrometers. Therefore, in order to give a thorough overview of the actual occurrence of each element in the considered scene, several spectra identifying minerals with different geophysical features are used as endmembers' library. Indeed, the overall endmember library $\underline{\underline{M}} = \{\underline{m}_r\}_{r=1,\ldots R}$ can be written as $\underline{\underline{M}} = \bigcup_{s=1}^{S} \underline{\underline{M}}_s$, where $\underline{\underline{M}}_s$ identifies the set of spectral signatures which can be associated with the s-th specific mineral compound. Thus, let $\hat{\alpha}_{sl}$ be the estimate of

the actual abundance of the *s*-th mineral over the *l*-th pixel. Then, it is possible to retrieve a thorough estimate of the each $\hat{\alpha}_{sl}$ as follows:

$$\hat{\alpha}_{sl} = \sum_{j:\underline{m}_j \underset{=}{\in} M_s} \frac{\hat{a}_{jl}}{\sum_{r=1}^{R} \hat{a}_{rl}} \qquad (4)$$

Experimental results in the following Section are then evaluated according to these metrics.

RESULTS

The IIM is a sagnac-based spatially modulated Fourier transform imaging spectrometer on-board the first lunar satellite of China, Chang'E-1 [10] [9] [15]. It mapped the lunar surface with a swath of 25.6 km and spatial resolution of 200 m from a polar orbit of 200 km altitude. Within the wavelength range of IIM, i.e., 480.9–946.8 nm, it has 32 continuous channels with a theoretical spectral resolution of 330 cm^{-1} (variable from the highest 7.5 nm at 480 nm to the lowest 29 nm at 946 nm in wavelength units) according to the Sparrow's criterion. The spectral resolution and wavelength position in the laboratory test with the gas laser and semiconductor laser shows that the actual resolution is about 355 cm^{-1} and maximal shift of 2.48 nm at 831.2 nm for the wavelength position The signal–to–noise (SNR) of the in-flight data, was evaluated with a simple mean/standard deviation method. Then, only 26 bands are kept to proceed with investigation [9].

We first tested the nonlinear spectral unmixing approach over the area where the Apollo 17 mission landed [4] [3]. The considered Chang'E-1 image on that region consists of 391 x 446 pixels and 26 bands. We used this first analysis to investigate the performance of architectures based on different spectral mixture models. Specifically, 72 spectral signatures of mafic elements collected from laboratory and experimental observations have been used as endmembers to feed the nonlinear spectral unmixing frameworks. Moreover, the endmembers have been pooled into nine groups of major mineral compounds, i.e., S = 9 in (4). These materials result from pure mafic elements [namely olivine (OL), plagioclase (PL), orthopyroxene (OPX) and clinopyroxene (CPX)] and mixtures of the aforesaid minerals [namely OL-OPX, OL-OPX-PL, OPX-CPX, OPX-CPX-OL, CPX-OL].

Indeed, we exploited the knowledge that has been acquired on the landing site in order to verify the accuracy of the estimated minerals' abundance distributions. Specifically, we focused on the orthopyroxene compound, which presence has been found to be especially relevant in the green box in Figure 1 by surface exploration. Figure 1(a) shows the mineral absorption that has been retrieved by analyzing the Voyager spectrometer records: it is thus possible to appreciate the distribution of this mafic mineral in blue and cyan.

Experimental results in Figure 2 report that the unmixing method obtained by 5-linear mixture model (5LMM) provides higher accuracy in estimating the abundance of orthopyroxene than linear or bilinear models. This result is somehow expected, since it is compliant with the capabilities of higher order nonlinear models to track sophisticated mixtures in spectrally and geometrically complex scenes. Furthermore, it is possible to appreciate that the 5LMM model is able to strongly determine and separate the abundance estimates, so that the blurriness produced by linear and low order nonlinear mixture models is dramatically reduced.

In the second performed test, we focused on a much wider region of Moon surface (Figure 3). The selected area is located around Laplace A and Helicon craters in sinus Iridum and Mare Imbrium. This portion of Moon surface is especially interesting because it identifies a general flat terrain, which can be eventually used as landing site for future missions. The Chang'E-1 dataset that has been taken into account consists of 2647 x 445 pixels

Several higher order nonlinear spectral unmixing models were considered. Moreover, we fed the spectral unmixing schemes with the spectral signatures identifying six major elements on Moon surface, i.e., FeO, TiO2, MgO, Al2O3, CaO and SiO2. In order to evaluate the actual ability of this

approach to detect and quantify the abundance distribution of these elements, we compared the retrieved abundance maps with those by the PLSR framework in [9].
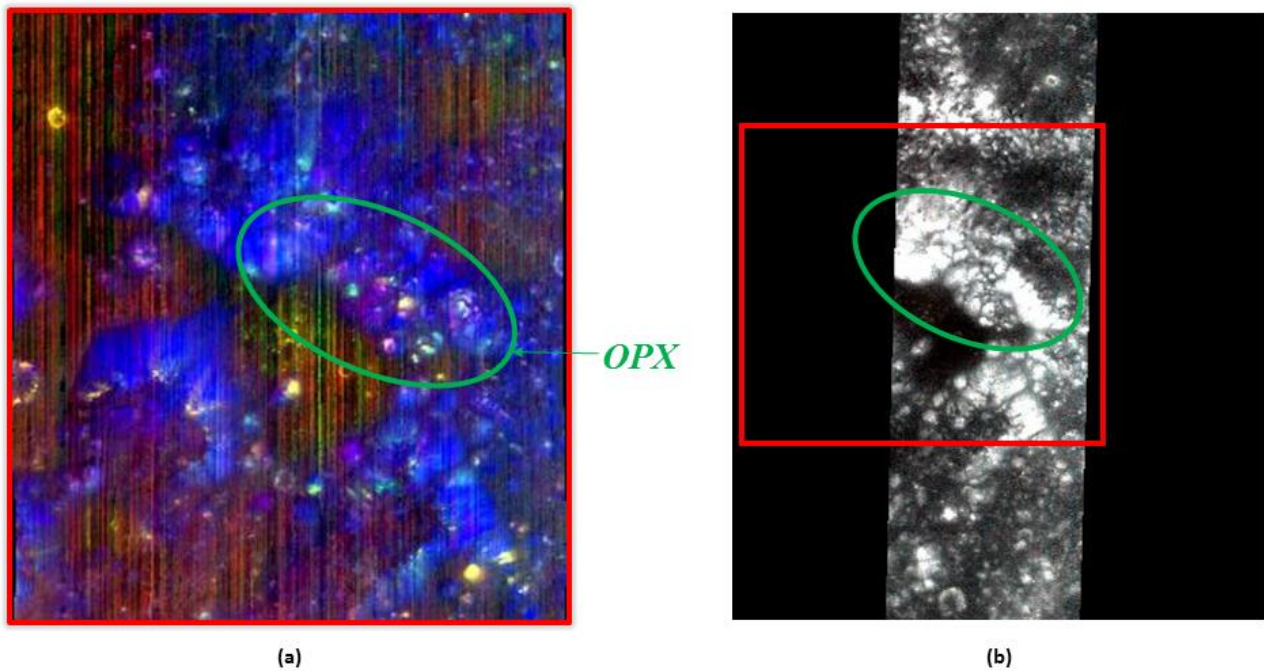

Figure 1 (a): mineral absorption map of the area of Apollo17 landing site. The green box highlights the area with the strong presence of orthopyroxene (light blue and cyan). (b): Chang'E-1 data over the same area (band 4).
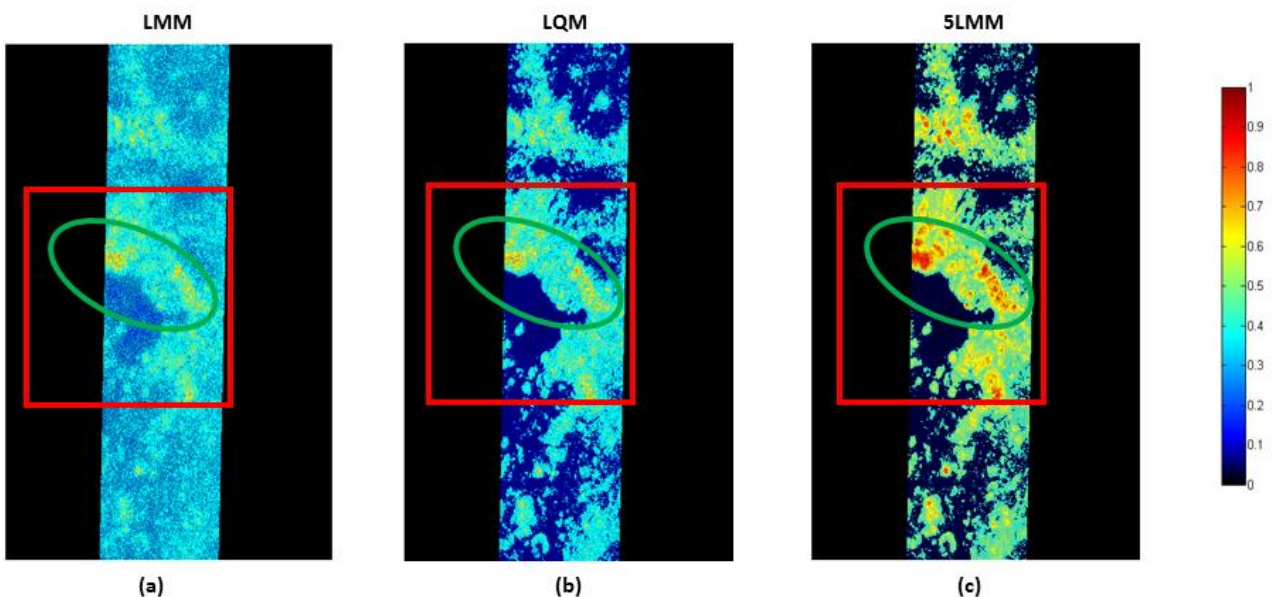

Figure 2: Orthopyroxene abundance maps for the area in fig.1 retrieved by means of linear , bilinear and 5-linear spectral unmixing models ((a), (b) and (c), respectively).

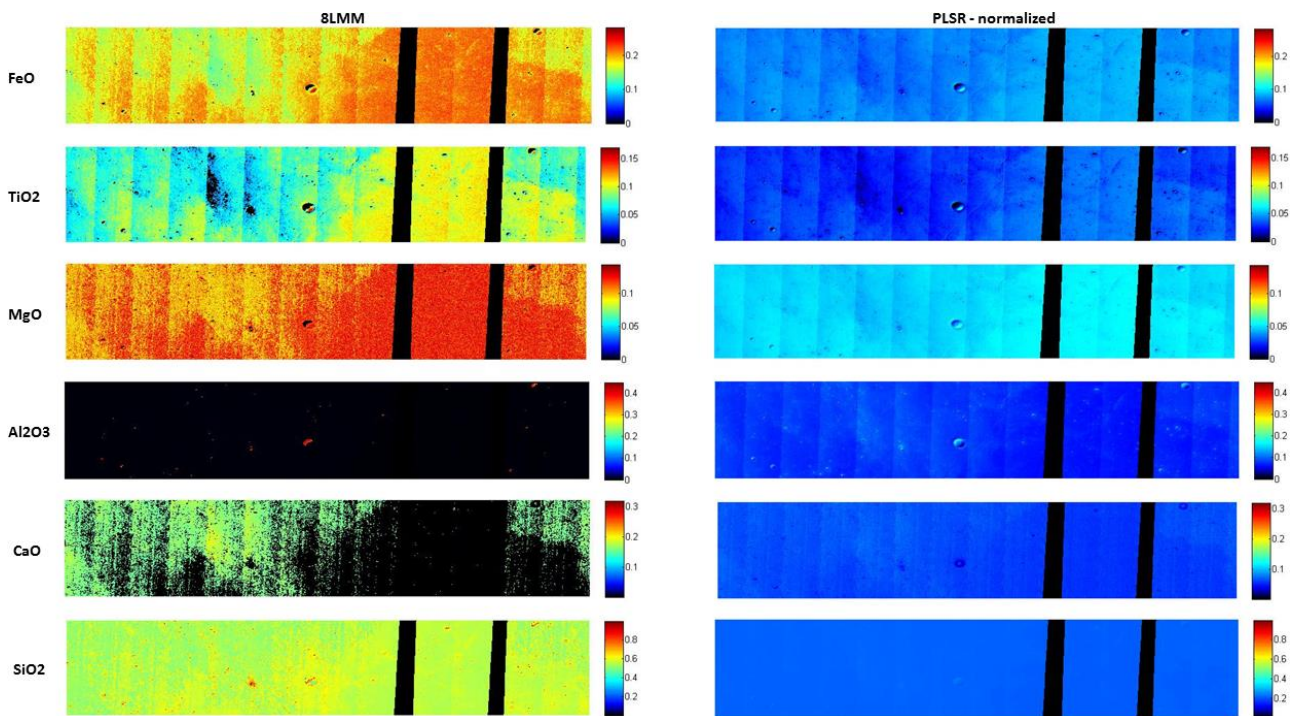*Figure 3: the region of the Moon surface considered as second test.*

Figure 4: Mineral abundance maps by spectral unmixing based on a 8-linear mixture model (a) in the area of fig.3, to be compared with those obtained by partial least squares regression in (b).

Figure 4 shows the results obtained using a 8-linear mixture model (8LMM). The approach based on non-linear spectral unmixing is able to accurately track the minerals' distribution, since the produced maps do not differ significantly from the PLSR outcomes. This aspect is further emphasized by Figure 5, where the error distributions for each mineral on the considered image is displayed. Moreover, the average error histogram in Figure 6 delivers even more insight on the actual performance of the proposed approach. Specifically, it is apparent that the error obtained for most of the considered endmembers is less than 10%, which represents a robust result from a statistical point of view. However, the average abundance error for SiO2 is greater than 30%. This effect can be explained taking into account the chemical properties of SiO2 itself. Specifically, SiO2 shows a non-orthorombic crystalline structure, which implies a very fine grain size of the SiO2 minerals on the surface. These properties cause strong nonlinear interaction on the reflectance contribution for the SiO2 minerals at a macroscopic scale. Thus, PLSR estimates might not be very accurate, since that framework definitely relies on the linearity of the minerals' reflectance [9].
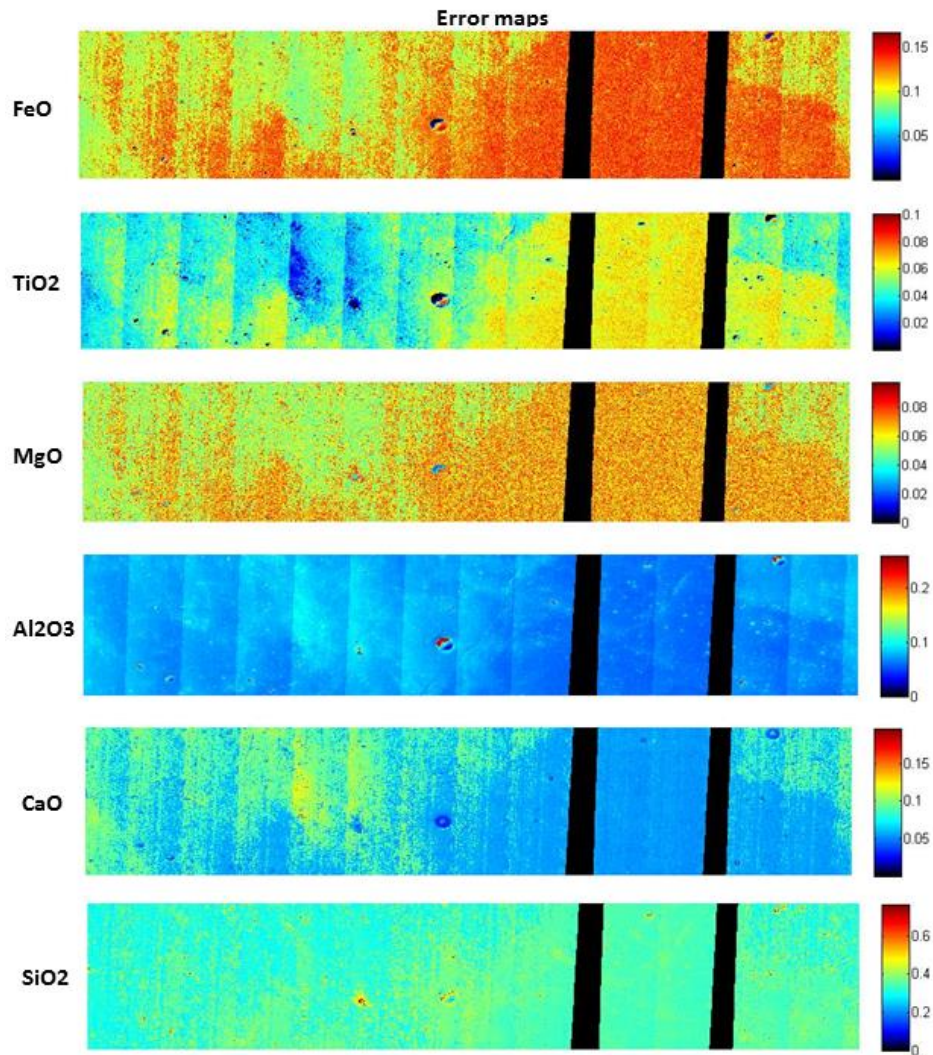
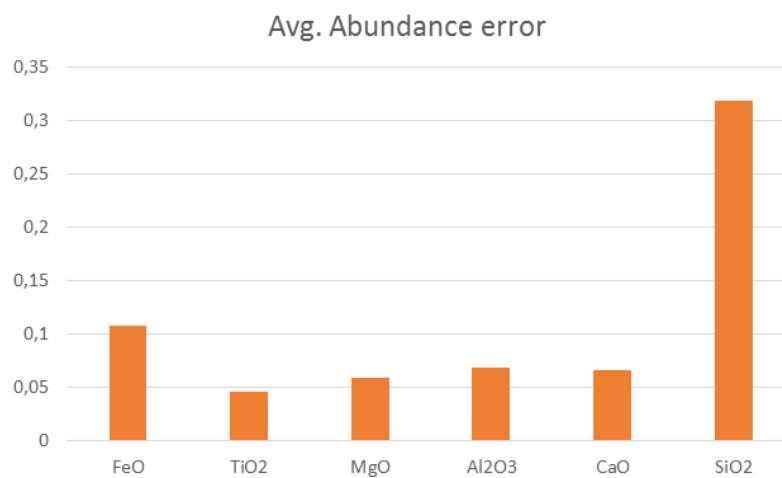*Figure 5: error distribution of the results in Figure 4 for each mineral.*

Figure 6: Average abundance error for each mineral in Figure 5.

CONCLUSIONS

In this paper, a framework for analyzing mineralogical composition of extraterrestrial planets has been provided. The proposed scheme, based on nonlinear spectral unmixing, is able to provide accurate assessment of mineral abundance distributions on the Moon surface. Furthermore, it provides detailed information on the surface geophysical composition. Experimental results show that the proposed approach is actually able to extract mafic mineral maps highly correlated to reference mineral distributions. Future works will focus on exploiting the results obtained from the proposed method to achieve higher-resolution high-accuracy quantification of the mafic.

ACKOWLEDGEMENTS

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