UPSCALING HIGH-RESOLUTION MINERALOGICAL ANALYSES TO ESTIMATE MINERAL ABUNDANCES IN DRILL CORE HYPERSPECTRAL DATA

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ABSTRACT

In this paper, we propose a supervised learning method for estimating mineral quantities in drill core hyperspectral data. Our proposed method links the high-resolution mineralogical analyses and hyperspectral data to learn a dictionary. The learned dictionary is then used for linear unmixing and estimating mineral abundances of the entire drill core sample. To evaluate the performance of the proposed method, we use a drill core data set, which is composed of the VNIR-SWIR hyperspectral data and high-resolution mineralogical analyses performed by a Scanning Electron Microscopy (SEM) instrument equipped with the Mineral Liberation Analysis (MLA) software. The quantitative and qualitative analysis of the experimental results shows that the proposed method provides reliable mineral quantity estimates.

***Index Terms*—** Hyperspectral drill core data, high-resolution mineralogical analysis, upscaling, dictionary learning.

1. INTRODUCTION

Drill cores are the main tool to discover mineral deposits and characterize the ore body in exploration campaigns. These cylindrical cores are a few inches wide and extracted by drilling holes into the Earth's subsurface to specific depths in the range of meters. The detailed analysis of drill cores allows geologists to obtain information on e.g., the lithology, mineralogy, and alteration zones [1]. Several laboratory and field techniques have been developed to support geologists for the drill core analysis. The Scanning Electron Microscopy (SEM) instrument integrated with the Mineral Liberation Analysis (MLA) software (i.e., SEM-MLA) [2] has been a successful and accurate analytical laboratory method to obtain high-resolution mineralogical information from drill core rock samples. Exploiting this technique, a geologist can reveal the mineralogical composition of polished thin sections of rock samples extracted along the drill cores.

Alternatively, hyperspectral imaging is recently exploited in the mining industry as a rapid and non-invasive field method to obtain mineralogical information. Hyperspectral sensors cover a wide range of the electromagnetic spectrum and record data in several tens of spectral bands. Since each mineral has unique spectral responses in specific portions of the electromagnetic spectrum, the spectral information contained in hyperspectral data can be used for mineral characterization [3, 4]. One of the important tasks in drill core hyperspectral data analysis is the determination of mineral quantities, so-called unmixing. For this purpose, several techniques have been suggested in the literature which are mostly based on the linear mixing model [5]. The main assumption of this model is that the spectrum of each hyperspectral data point is the linear combination of few representative minerals spectra, so-called endmembers, weighted by each mineral's fractional abundance. Typically, the unmixing techniques assume that a dictionary composed of a set of pure spectral signatures (i.e., endmembers) is available. Thus, in such methods, the performance of the abundance estimation strictly relies on the selection of the endmembers. However, in real scenarios, the determination of the number of endmembers and extraction of them are challenging tasks, especially, in drill core hyperspectral data which are highly mixed and hardly contain pure pixels.

In this paper, we consider a different scenario for estimating mineral quantities in drill core hyperspectral data. We first compute mineral abundances for a small area of a drill core by resampling of the SEM-MLA image to the resolution of the hyperspectral data. Then, we link the mineral abundances in this small area to their corresponding spectra and learn a dictionary. Finally, we use the learned dictionary for linear unmixing and estimating mineral abundances for the rest of hyperspectral data points. Our proposed method exploits the complementary information of the SEM-MLA and hyperspectral imaging techniques for estimating mineral quantities.

The rest of the paper is organized as follows. Section 2 describes the methodological framework. Section 3 presents data description, experimental results, and discussions. Finally, Section 4 concludes with some remarks and hints at possible future research lines.

2. METHODOLOGICAL FRAMEWORK

Let us focus on the small area of the drill core, which is subjected to the SEM-MLA analysis, and denote the drill core hyperspectral image in this area as $\mathbf{X} \equiv (\mathbf{x}_1, \mathbf{x}_2, ..., \mathbf{x}_n)$, composed of n number of pixels. Each $\mathbf{x}_i$, $i = 1, \ldots, n$, is a real positive spectral vector, which is recorded in d spectral bands. Let $\mathbf{Y} \equiv (\mathbf{y}_1, \ldots, \mathbf{y}_n)$ be the corresponding fractional abundances, where $\mathbf{y}_i \equiv [y_{i1}, y_{i2}, \ldots, y_{ir}]^T$, and r is the number of minerals. We also consider the usual constraints $\sum_j y_{ij} = 1$ and $\forall j : y_{ij} > 0$.

Based on the linear mixture model, the spectra $\mathbf{X}$ can be linked with the fractional abundances $\mathbf{Y}$ by solving the following problem:

$$\min \|\mathbf{X} - \mathbf{D}\mathbf{Y}\|_2 \;\; s.t. \, \mathbf{D} \geq 0, \tag{1}$$

where $\mathbf{D}$ represents a dictionary, which can be used for a linear unmixing. The equation (1) searches for the optimal $\mathbf{D}$ in a least squares sense. Note that non-negativity constraint is needed since both matrixes $\mathbf{X}$ and $\mathbf{Y}$ are composed of non-negative values. This problem can be solved using, for example, the strategy presented in [6]. When the optimal $\mathbf{D}$ is computed, it can be used in a linear unmixing algorithm to estimate the abundance fractions for the entire drill core hyperspectral data.

3. EXPERIMENTAL RESULTS

To evaluate the performance of the proposed method, we consider the drill core sample shown in Fig. 1. From the entire drill core sample, the VNIR-SWIR hyperspectral data of size 33×189 pixels and 450 spectral bands of wavelengths from 380 nm to 2500 nm were acquired by a SisuRock drill core scanner equipped with an AisaFenix sensor. Moreover, the high-resolution mineralogical analysis was performed on a representative region selected by a geologist using an FEI Quanta 650 F field emission SEM instrument, equipped with two X-ray detectors and the MLA software. As shown in Fig. 1, the original MLA mineral map contains indexes for 22 minerals.

Considering the spatial resolution of the hyperspectral data and SEM-MLA image, each hyperspectral pixel covers an area of 1.5×1.5 mm^2, which is characterized by about 250000 pixels in the SEM-MLA image. The fractional abundances $\mathbf{y}_i$ for each hyperspectral pixel $\mathbf{x}_i$, $i = 1, \ldots, n$, were computed by considering the frequency of the existing minerals in the corresponding region of the SEM-MLA image. Hence, $n = 373$ fractional abundance vectors were obtained from the SEM-MLA image. Moreover, to have more consistent results, we considered a threshold of 250000 pixels (i.e., a hyperspectral pixel size) for discarding minerals which have a very low frequency in the original SEM-MLA image. We also grouped minerals with insignificant absorption features in the VNIR-SWIR ranges as others. Taking these considerations, the following $r = 6$ classes were chosen: white mica (Wmca), biotite (Bt), chlorite (Chl), amphiboles (Amp), gypsum (Gp), and other-minerals (OMs).

In addition to the proposed supervised dictionary learning based technique, we also applied the multivariate linear regression model [7, 8] learn a direct mapping between the high-resolution mineralogical analyses and hyperspectral data in the SEM-MLA region. The learned regression model was then used to estimate mineral abundances for the rest of hyperspectral data points.

SEM-MLA image (Fig. 1) reveals that the veins are mainly composed of quartz, white mica and gypsum, whereas the matrix is mainly composed of k-feldspar and plagioclase minerals, which have been mostly altered to white mica, chlorite, and biotite. As can be observed in Fig. 2, this detailed mineralogical information has been well upscaled to the entire drill core using hyperspectral data and applying our proposed method. For example, using our proposed method, the higher quantities in the veins were estimated for the Wmca, and OMs classes. This follows the observed alteration style quartz-white mica-pyrite in the SEM-MLA region. There is also a gypsum vein with a thick white mica alteration halo, which has been very well quantified. In comparison, the direct mapping technique has not shown satisfactory results. For example, in the veins, it has overestimated the amount of Gp and underestimated the presence of Wmca.

For quantitatively evaluating the proposed method, we randomly selected 50% of the fractional abundance vectors for estimating the dictionary matrix $\mathbf{D}$ and considered the rest for validation. We repeated this experiment 20 times. The average of the abundance root mean squared errors (RMSE) of these experiments were 0.12 and 0.10 for the direct mapping using multivariate linear regression model and the proposed method, respectively. This shows the great performance of our proposed method.

4. CONCLUSION AND REMARKS

In this paper we presented a supervised learning technique to extract mineral quantitative information from drill core hyperspectral data. Our proposed method learns a dictionary by linking the mineral abundances extracted from the high-resolution mineralogical analyses to their corresponding spectra. The learned dictionary is then used in a linear unmixing algorithm to estimate mineral abundances for the rest of the hyperspectral data points. In this work, we used SEM-MLA to perform high-resolution mineralogical analysis and prepare the training data. The experimental results, which have been conducted on a drill core data set composed of hyperspectral and SEM-MLA data, showed that the proposed method provides reliable mineral quantities. However, it is important to mention that the performance of our proposed method strictly depends on the selection of the SEM-MLA region.

As part of our future work, we will explore different strategies for supervised dictionary learning, specially, spectral-spatial approaches.

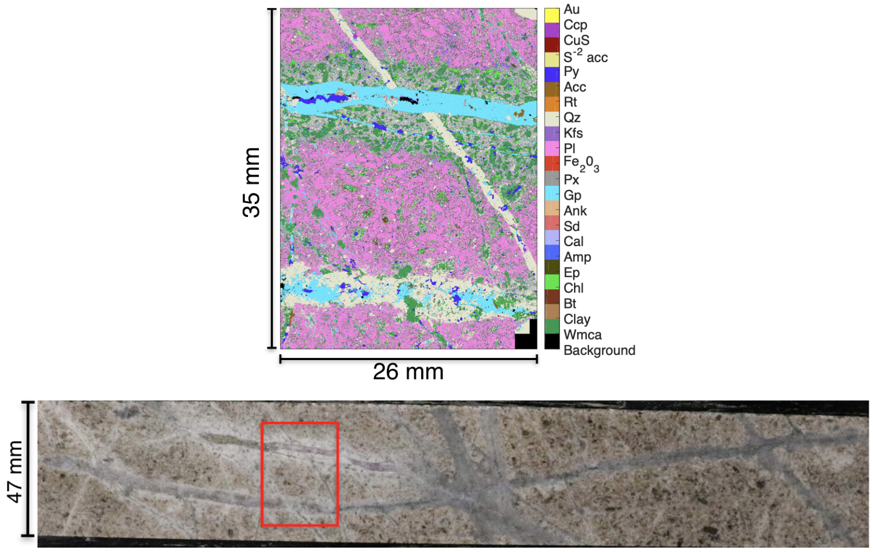

Fig. 1. RGB image of the drill core sample and the original SEM-MLA mineral map of the area indicated with a red rectangle. Mineral abbreviations after [9].

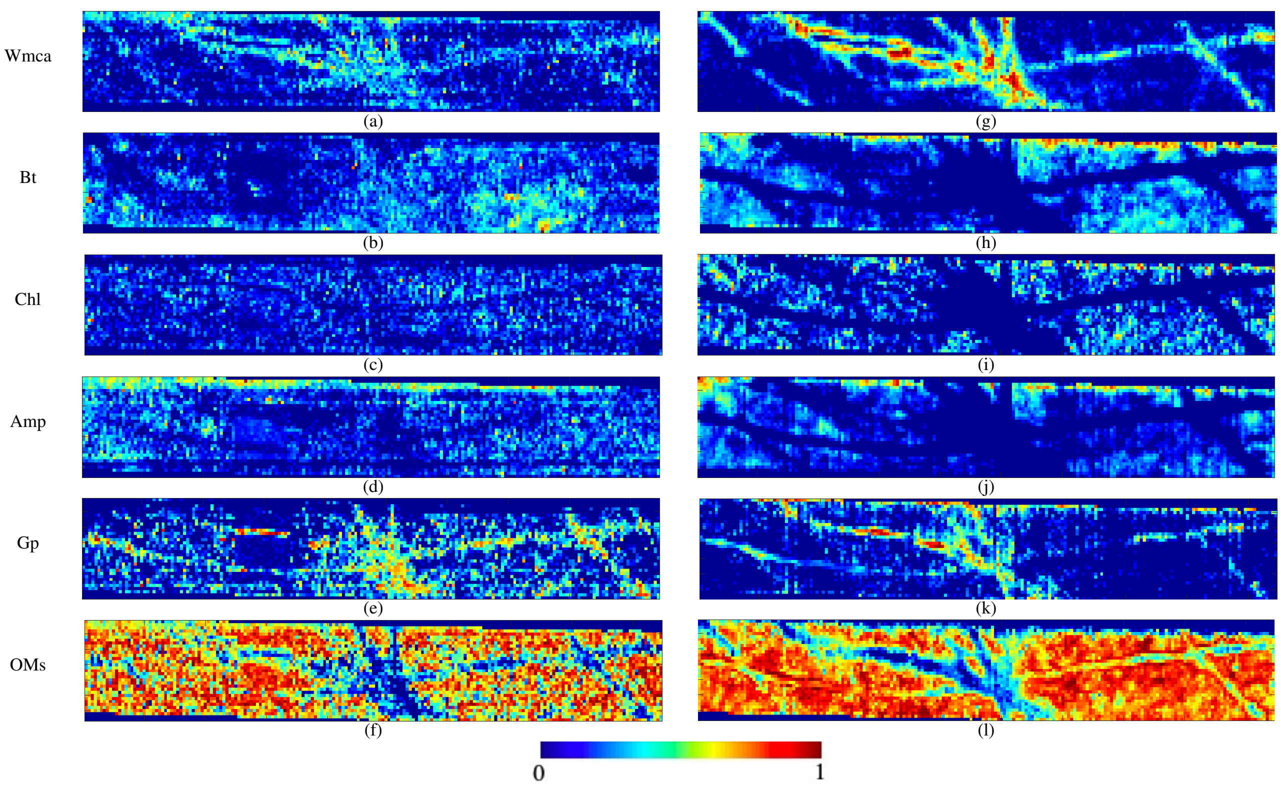

Fig. 2. Minerals abundance maps estimated by upscaling the high-resolution mineralogical analyses with (a)-(f) the multivariate linear regression model (direct mapping), (e)-(l) the proposed method.

5. ACKNOWLEDGEMENT

Special thanks go to Laura Tusa for conducting SEM-MLA analyses and her kind help in interpretation of the experimental results.

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