EXTRACTION OF STRUCTURAL AND MINERALOGICAL FEATURES FROM HYPERSPECTRAL DRILL-CORE SCANS

Laura Tusa[1], Louis Andreani[1], Eric Pohl[2], I. Cecilia Contreras[1], Mahdi Khodadadzadeh[1], Richard Gloaguen[1], Jens Gutzmer[1,3]

[1]Helmholtz-Zentrum Dresden-Rossendorf,
Helmholtz Institute Freiberg for Resource Technology, Germany
[2]LSCE/IPSL, CEA-CNRS-UVSQ, Université Paris-Saclay, Gif-sur-Yvette, France
[3]Technische Universität Bergakademie Freiberg, Germany

ABSTRACT

For vein hosted mineralization such as encountered in porphyry systems, the documentation of the main alteration assemblages associated with specific vein generations is essential in understanding the geometry of the mineralized body. Hence, mineralogical and structural information are highly relevant for characterizing the system. In this paper, we present an approach for the extraction of both mineralogical and structural information from hyperspectral scans. We propose a parallel framework which includes a typical mineral mapping technique for the extraction of mineralogical information as well as a ridge detection method, for the extraction of veins, applied on mineral abundance maps. In the proposed framework, the abundance maps are obtained from hyperspectral VNIR-SWIR drill-core scans using a linear spectral unmixing technique. Drill cores hosting porphyry stockwork type mineralization are used for the evaluation of the proposed technique and the experimental results show that the method offers a tool for accurately characterizing the mineralized body.

Index Terms – Core scanning, hyperspectral imaging, image segmentation, feature extraction, mineral mapping.

1. INTRODUCTION

Underground mineral potential is assessed using extensive drilling campaigns. Traditionally, the aim of these campaigns is to model the distribution of the mineralization and hydrothermal alteration in order to understand the genesis, geometry and zonality of mineral deposits [1]–[3]. Core logging is the common approach [4], [5], which consist of a visual analysis and description of the drill core. However, such techniques can present limitations in the identification of similar mineral phases. Additionally, while using this approach, the identification and quantification of structural features, such as veins, is slow and frequently imperiled by the subjectivity of the observer.

Hyperspectral images allow the identification of the main secondary mineral phases and the analysis of their distribution either as pervasive alteration or as vein halos. Each vein type tends to display a specific signature in the VNIR-SWIR region of the electromagnetic spectrum, given by either its composition or by the composition of its alteration halo [6], [7]. Although some works exist on the automatic characterization of textures [8] and vein detection [9] for the drill core data, more needs to be explored regarding the automated extraction of structural features together with the analysis of mineral alteration assemblages. For this reason, our aim is to develop new methods which respond to the need for a rapid, automated and precise extraction of both mineralogical and structural information from cores.

We propose to complement the traditional mineral mapping based on hyperspectral VNIR/SWIR data from drill-core scanners with an analysis of structural information. The main contribution of our approach is that it provides a unified framework to link mineralogical and structural features. The lineament extraction is performed on the abundance maps obtained by linear spectral unmixing using the endmembers identified in the n-Dimensional visualizer. The abundance maps carry mineralogical information of the vein or vein alteration halo. The extracted structural features are finally joined with the mineral map derived from a standard classification technique.

The extraction of such information supports a more accurate quantification and thus evaluation of different vein generations. Therefore, the integration of such new methodologies in exploration campaigns would allow for better and faster exploration targeting based on key mineral assemblages and structural features.

2. DATA PROCESSING

As shown in Fig. 1 data processing is performed in a parallel framework consisting of two branches: mineral mapping and extraction of structural features.

3.1. <u>Mineral Mapping</u>

The mapping of mineral assemblages is performed using ENVI version 5.1 (Exelis Visual Information Solutions, Boulder, Colorado) software. First, we used a minimum noise fraction (MNF) transform process in order to reduce the dimensionality of the data. We then used pixel purity index (PPI) in order to determine and locate the purest pixels in the dataset [10]. Further, we performed an endmember extraction using ENVI's n-Dimensional visualizer, which allows the visualization of endmember clusters consisting of the purest pixels in an n-dimensional space by representing the selected number of relevant MNF bands. The coordinates of each point represent the reflectance of a specific pixel in each of the bands. With the selected endmembers we perform a mineral mapping using ENVI's spectral angle mapper (SAM) algorithm. Finally, we use a linear spectral unmixing algorithm [11], based on the extracted endmembers in order to develop mineral abundance maps which are then used for the extraction of linear features.

3.2. Extraction of Linear Features

We use a ridge detection algorithm in order to extract linear features such as mineralized veins from the abundance maps. The basic idea behind this algorithm is to locate the points of maximum curvature in an image which correspond to the mineral signatures of specific vein types obtained from the endmember extraction.

One common approach to analyze the curvature of an image is to use an eigenvalue analysis of the Hessian matrix [12], [13]. The Hessian matrix is a 2×2 matrix composed of second-order partial derivatives of the input image while the second-order partial derivatives are defined as a convolution with derivatives of Gaussian filter at scale σ.

The eigenvalue analysis of the Hessian matrix allows to extract the principal directions and magnitude in which the local second order structure of the image can be decomposed. Each pixel is associated to a set of eigenvectors such as $|\lambda 1| \leq |\lambda 2|$. Linear features are characterized by a very small magnitude of $\lambda 1$ (ideally close to zero) and a large magnitude of $\lambda 2$, while point features will be characterized by similar magnitudes of $\lambda 1$ and $\lambda 2$ and features without preferential directions will have low magnitudes for both $\lambda 1$ and $\lambda 2$.

In order to identify the linear features of the image we then use the approach developed by Steger [14] which identifies points with maximum curvature (i.e. ridges) based on the absolute magnitude of eigenvectors. Identified points are then connected by lines.

Finally, a threshold based on the absolute magnitude of eigenvectors is used in order to remove weak lines (i.e. associated to a low curvature). Lines associated to a magnitude greater than the threshold are kept, while lines below this threshold are only kept if connected to the previous ones.

Lines extracted from a noisy image are often tortuous and disconnected, which might hinder further analyses such as the extraction of their orientations. Thus, a simplification as well as a merging and linking of the lines may be necessary. Lines are simplified using the approach from Visvalingam and Whyatt [15], which iteratively removes points which results in least areal displacement from lines.

3. EXPERIMENTAL RESULTS

3.1. Data acquisition

For testing the mentioned method, drill-cores hosting porphyry type veins are used. The drill-core samples were scanned using a SisuROCK drill-core scanner equipped with an AisaFENIX VNIR-SWIR hyperspectral sensor. The spectral range of the camera is 380 to 2500 nm with a spectral resolution of 3.5 nm in the VNIR and 12 nm in the SWIR. The total number of hyperspectral bands in the resulting image is 450. The scanning was performed using a frame rate of 15 fps and a scanning speed of 25.06 mm/s. 4x spectral binning was chosen for VNIR and 1x for SWIR. The chosen integration time for the VNIR was 15 s while for the SWIR 4 s. The spatial resolution of the resulting hyperspectral scans is 1.7 mm/pixel.

3.2. Experimental results

We present here, as an example, the results from a core sample collected from a porphyry system. The pervasive alteration is chlorite-white mica dominant and two main vein types are present as follows: the first one consists of quartz and hosts a white mica dominant halo and the second one consists dominantly of gypsum-anhydrite and fluorite, also with a white mica alteration halo. The differentiation between these two types can be visually made based on the purple fluorite signature in the VNIR area of the electromagnetic spectrum and on the specific gypsum absorption features starting at 1443 nm. The white mica shows specific absorption features at 1396 nm and 2191 nm and the chlorite at 2246 nm. These endmember spectra are shown in Fig. 2.

The results of the mineral mapping performed with the spectral angel mapper using the shown endmember spectra can be seen in Fig. 3 (B) next to the RGB image of the core Fig. 3 (A).

We applied the lineament extraction algorithms on the abundance maps of the white mica (Fig. 4 (A)) and white mica-gypsum-fluorite (Fig. 4 (D)) main alteration assemblages. Maximum absolute magnitudes of eigenvectors produced using an input $\sigma = 8$ are shown in Fig. 4 (B) and 4 (E). We extracted the linear features based on a threshold magnitude of 0.45 (Fig. 4 (C) and 4 (F)). Fig. 4 (H) shows extracted features after we applied the simplification and linking processes. The complementarity of the two approaches can be proven by superposing the extracted features over the simplified mineral map (Fig. 4 (I)).

We observe a good match for visually detected veins on the core and the extracted linear features where the veins stand alone or show simple cross-cutting relationships. However, some limitations appear. One of them is related to the parameter σ used for the Gaussian convolution kernel. This parameter is adjusted to target a certain range of thicknesses. Therefore, veins which are thicker or thinner may be either too much or not enough smoothened. This problem may be tackled by using a range of σ. Another limitation is related to the spatial resolution of the input data, which does not allow the precise detection of fine veins and vein clusters. Very fine veins show mixed pixels with small compositional variation and thus cannot be detected by the endmember analysis methods used until this point. In a similar way, noise associated to endmember analysis complicates the extraction of vein clusters.

The automation of the endmember extractions and vein detection together with the implementation of a protocol to express the alteration and vein distribution as numerical parameters would allow for better and faster 3D modelling and target generation.

4. CONCLUSIONS AND OUTLOOK

In this paper, we have proposed a new methodology to integrate the extraction of mineralogical and structural information from hyperspectral images that allows an easy correspondence between the mineral assemblages and structural features in a mineralized body. The methodology starts with the typical mineral mapping chain: dimensionality reduction using the minimum noise fraction process (MNF), an endmember extraction step joining pixel purity index and the n-Dimensional Visualizer, and a linear spectral unmixing algorithm. All this is then integrated with a ridge algorithm for the lineament extraction of vein features. This algorithm locates the points of maximum curvature in the image and then these points are connected by lines.

The results show that this methodology offers a good match between the visually observed veins on the core, the mineral alteration maps and the extracted linear features. However, improvements in mapping thicker and thinner veins can be done by using a range of σ parameter used for the Gaussian convolution kernel. Also, the improvement of the endmember extraction and unmixing methods could facilitate the linear feature extraction process. Since we would like to automate this method, as part of our future work, we will introduce a machine learning approach in the endmember extraction, unmixing and mineral mapping chain. Then, resulted abundances will be used for vein feature extraction.

5. REFERENCES

[1] F. F. Sabins, "Remote sensing for mineral exploration," *Ore Geol. Rev.*, vol. 14, no. 3–4, pp. 157–183, 1999.

[2] W. M. Calvin and E. L. Pace, "Mapping alteration in geothermal drill core using a field portable spectroradiometer," *Geothermics*, vol. 61, pp. 12–23, 2016.

[3] E. F. Littlefield and W. M. Calvin, "Geothermal exploration using imaging spectrometer data over Fish Lake Valley, Nevada," *Remote Sens. Environ.*, vol. 140, pp. 509–518, 2014.

[4] J. F. Huntington *et al.*, "Automated mineralogical core logging at the Emmie Bluff iron oxide- copper- gold Prospect," *Mesa J.*, vol. 41, no. April, pp. 38–44, 2006.

[5] M. Berry, G. Pope, R. Carlson, F. O'Brien, J. Leigh, and M. Pilkington, "Drilling for Geology II. Extended Abstracts," in *Australian Institute of Geoscientists.*, 2017, no. 64.

[6] R. N. Clark, "Spectroscopy of rocks and minerals, and principles of spectroscopy," in *Remote sensing for the earth sciences: Manual of remote sensing*, vol. 3, John Wiley & Sons, Inc, 1999, pp. 3–58.

[7] R. N. Clark *et al.*, "Mineral mapping and applications of imaging spectroscopy," *Int. Geosci. Remote Sens. Symp.*, pp. 1986–1989, 2006.

[8] G. M. Leigh, "Automatic ore texture analysis for process mineralogy," in *Ninth International Congress for Applied Mineralogy. ICAM Australia*, 2008, pp. 433–435.

[9] D. Wang *et al.*, "Automated vein detection for drill core analysis by fusion of hyperspectral and visible image data," *M2VIP 2016 - Proc. 23rd Int. Conf. Mechatronics Mach. Vis. Pract.*, 2017.

[10] J. W. Boardman, F. a Krusel, and R. O. Green, "Mapping target signatures via partial unmixing of AVIRIS data," *Jet Propuls.*, no. 23, pp. 23–26, 1993.

[11] H. . Li and C. I. Chang, "Linear spectral unmixing using least squares error, orthogonal projection and simplex volume for hyperspectral images," *7th Work. Hyperspectral Image Signal Process. Evol. Remote Sens. (WHISPERS), Tokyo*, pp. 1–4, 2015.

[12] A. . Frangi, W. . Niessen, K. . Vincken, and M. . Viergever, "Multiscale vessel enhancement filtering," *Proc. Med. Image Comput. Comput. Interv. (MICCAI '98)*, pp. 130–137, 1998.

[13] J. Jin, L. Yang, X. Shang, and M. Ding, "Vascular Tree Segmentation in Medical Images Using Hessian-Based Multiscale Filtering and Level Set Method," *Comput. Math. Methods Med.*, p. 9, 2013.

[14] C. Steger, "An unbiased detector of curvilinear structures," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 20(2), pp. 113–125, 1998.

[15] M. Visvalingam and J. D. Whyatt, "Line Generalisation by Repeated Elimination of Points," *Cartogr. J.*, vol. 30, pp. 46–51, 1993.

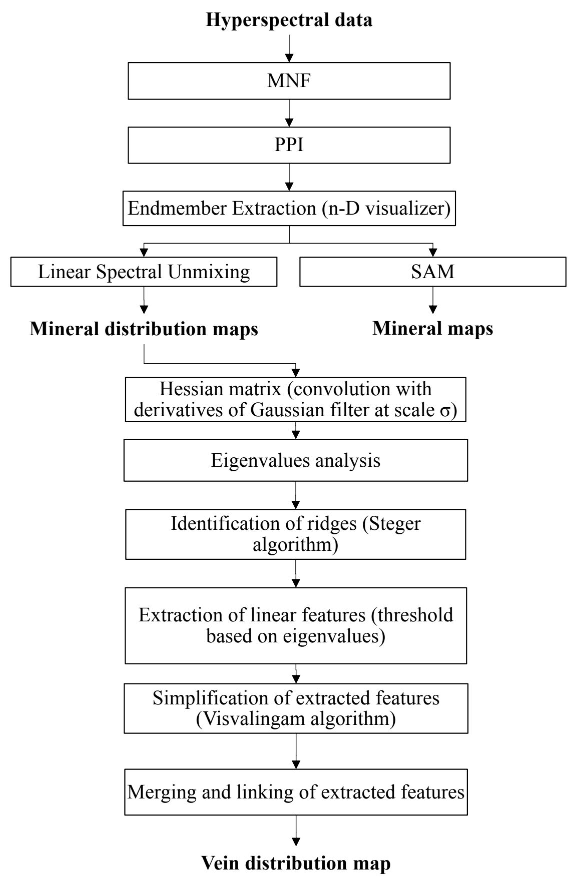

Fig. 1. Flowchart illustrating the proposed methodology.

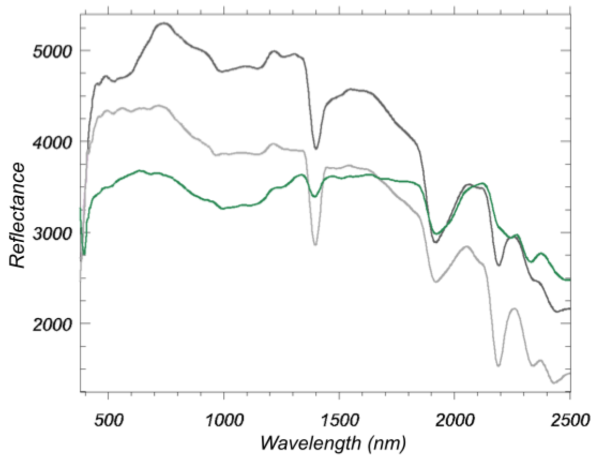

Fig. 2. Endmember spectra: Green – chlorite-white mica pervasive alteration; dark grey – white mica-gypsum-fluorite; light grey – white mica.

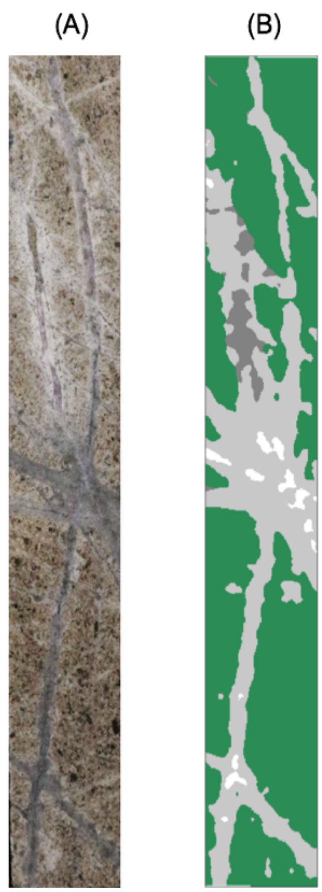

Fig. 3. (A) – RGB image of core sample; (B) – mineral map of core sample where, green – chlorite-white mica pervasive alteration, dark grey – white mica-gypsum-fluorite, light grey – white mica, white - aspectral. The core width is 47 mm.

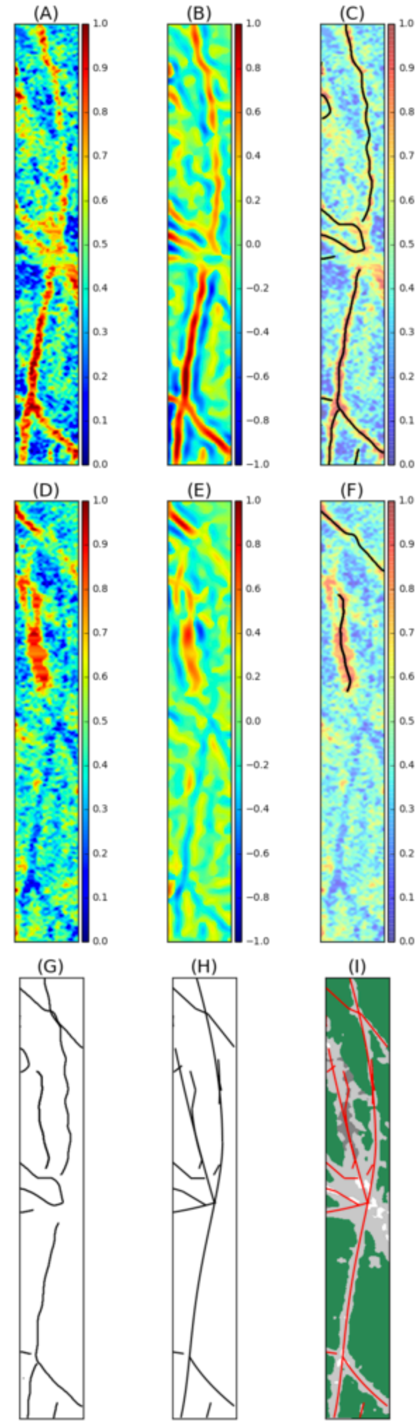

Fig. 4. Endmember abundance, maximum absolute magnitude of eigenvectors and extracted linear features for white mica (A, B, C) and white mica-gypsum-fluorite (D, E, F) assemblages; (G) and (H) show extracted features before and after the simplification and merging process. (I) shows extracted features overlaying the simplified mineral map (Figure 3B).