Unmixing-based feature extraction for mineral mapping

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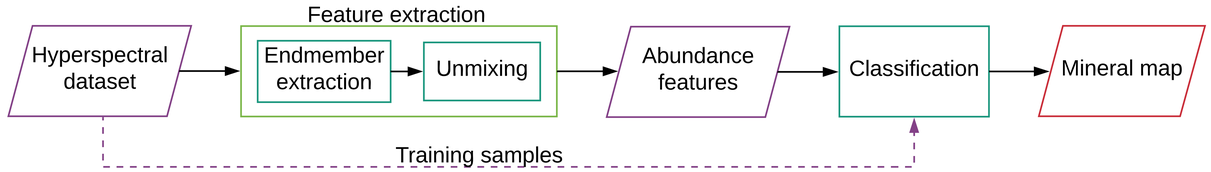
Motivation

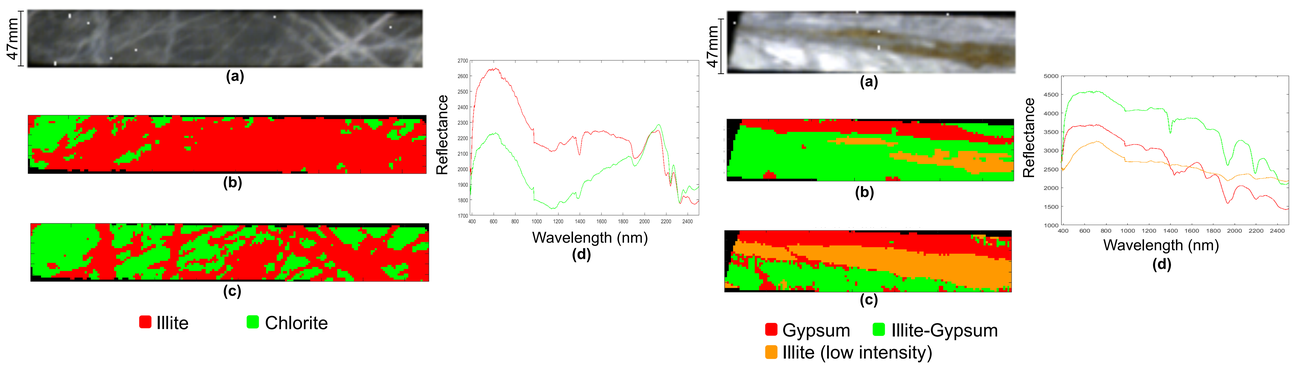
- Hyperspectral data offer a tool to obtain valuable information in drill cores, which can be used to identify minerals and accurately map their alteration phases and spatial patterns.
- Mineral mapping is usually achieved by applying an endmember extraction technique followed by a spectral similarity measure (e.g., Spectral Angel Mapper (SAM)).
- In this work, we propose a machine learning technique to map minerals. We suggest to use abundance features as input for an unsupervised or supervised classification algorithm [1].

Proposed technique

- Flowchart for the proposed technique:

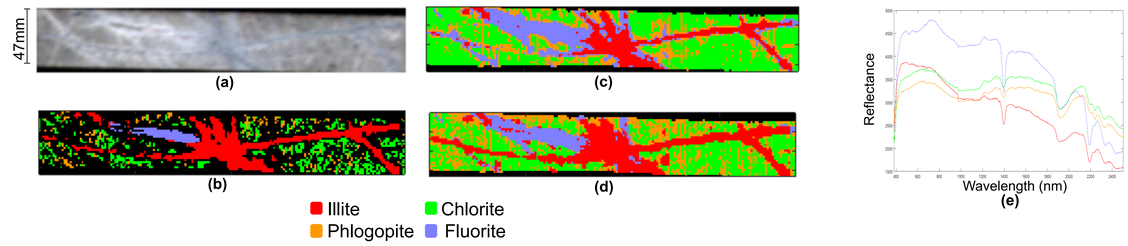


Unsupervised classification



(a) RGB composition of drill core hyperspectral image, (b) mineral maps obtained by using N-Findr algorithm [2] to extract endmembers and Spectral Angle Mapper to match pixels to endmembers spectra, (c) mineral maps obtained by using the chain of N-Findr and Fully Constraint Linear Spectral Unmixing algorithms to generate abundance features followed by K-means for the unsupervised classification, (d) mean spectra of all classes

Supervised classification



(a) RGB composition of drill core hyperspectral image, (b) reference data of the HSI generated by a comprehensive visual analysis, (c) mineral map obtained by using N-Findr algorithm [2] to extract endmembers and Spectral Angle Mapper to match pixels to endmembers spectra, (d) mineral maps obtained by using the chain of N-Findr and Fully Constraint Linear Spectral Unmixing algorithms to generate abundance features followed by Support Vector Machines (SVM) for the supervised classification, (e) mean spectra of all classes

Classification accuracies for 50 training samples per class(%)

	Methods	
Accuracies	**SAM**	**Abundance features + SVM**
Overall	72.24 ± 1.4	93.32 ± 0.6
Average	63.66 ± 2.2	92.84 ± 0.7

Conclusions

- We conclude that the proposed machine learning technique provides qualitatively and quantitatively accurate mineral maps.
- We show that the abundance features are well suited for the purpose of mineral mapping since they have physical meaning related to the abundances of the available minerals in each sample.
- Both proposed techniques, i.e., unsupervised and supervised, are with minimal human interaction and allow the quick automatic mapping of minerals in typically large amount of drill core hyperspectral data.

[1] Dópido, I., Villa, A., Plaza, A., & Gamba, P. (2012). A Quantitative and Comparative Assessment of Unmixing-Based Feature Extraction Techniques for Hyperspectral Image Classification. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 5(2), 421–435.

[2] E. Winter, M. (1990). N-FINDR: An Algorithm for Fast Autonomous Spectral Endmember Determination in Hyperspectral Data. Image Spectrometry V, Proc. SPIE, 3753, 266–275.

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