

### Mineral Identification And Characterization: An Integrated Approach To Recover Mineralogical Information From Hyperspectral Images

Ronan Rialland, Rodolphe Marion, V. Carrere, Charles Soussen,

Jean-Philippe Poli

#### ► To cite this version:

Ronan Rialland, Rodolphe Marion, V. Carrere, Charles Soussen, Jean-Philippe Poli. Mineral Identification And Characterization: An Integrated Approach To Recover Mineralogical Information From Hyperspectral Images. 11th EARSeL SIG IS Workshop, Feb 2019, Brno, Czech Republic. , 2019. hal-02861548

#### HAL Id: hal-02861548 https://centralesupelec.hal.science/hal-02861548v1

Submitted on 9 Jun2020

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers. L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

# Mineral Identification And Characterization: An Integrated Approach To Recover Mineralogical Information From Hyperspectral Images

Rialland, Ronan<sup>1</sup>; Marion, Rodolphe<sup>1</sup>; Carrère, Véronique<sup>2</sup>; Soussen, Charles<sup>3</sup>; Poli, Jean-Philippe<sup>4</sup> <sup>1</sup>Commissariat à l'Energie Atomique et aux énergies alternatives, CEA/DAM/DIF, F-91297 Arpajon, France; <sup>2</sup>UMR-CNRS 6112 - LPG Nantes, Université de Nantes, 2 rue de la Houssinière, BP 92208, 44322 Nantes CEDEX 3, France; <sup>3</sup>L2S, CentraleSupélec-CNRS-Université Paris-Sud, Université Paris-Saclay, 91192 Gif-sur-Yvette, France; <sup>4</sup>CEA, LIST, Data Analysis and System Intelligence Laboratory, 91191 Gif-sur-Yvette cedex, France;



## Introduction and objectives

- Integrated and automatic procedure for mineral mapping from airborne and spaceborne hyperspectral images
- **Mineral reflectance spectra decomposition** in the **VNIR/SWIR** using EGO model (Exponential Gaussian Optimization)
- **Noise model** evolution for recent spectrometers
- **Identification procedure** from estimated parameters

## AGM (Automatized Gaussian Model) procedure [1]

### AGM flowchart Database (EGO parameters Reflectance hyperspectral Atmospheric conditions and variability) for each and sensor characteristics image selected mineral

## Noise estimation (HYNPE [5])

1) Signal and noise separation: HYSIME [6]

2) Noise parameter initialization: Methods of Moments

3) Noise parameter estimation: Maximum likelihood



Saturation	/	/	/	-10
Sample - Method	Dolomite – [11]	Dolomite – MGM	Dolomite – EGO (without saturation)	Dolomite – EGO
Center	2.32 (theory) – 2.315 (measure)	2.30195	2.31275	2.31306
Amplitude	-0.32682	-0.259494	-0.287883	-0.254443
Width	0.085	0.041663	0.036179	0.0270031
Asymmetry	≈ -0.45	/	0.278652	0.192566
Saturation	/	/	/	3.70758

• EGO model better fits SWIR absorptions and is sufficient to discriminate calcite

• Estimated parameters might loose some meaning (width, saturation, asymmetry)

≈ -0.4

Asymmetr

from dolomite

- Total noise evolution: increasing SNR makes mineral identification easier
- For recent spectrometers, noise is not totally independent from signal
- Main noise sources and their impact:
  - Dark current  $\Rightarrow$  independent noise
  - Photon noise  $\Rightarrow$  dependent noise

Estimation depends on the radiance of the image (high radiance implies high photon noise)

Future works

- Each mineral is defined by a set of parameters  $(P_1, ..., P_M)$  and an expert rule to ensure the meaning of the identification
- Identify the mineral by comparing database parameters to the estimated ones  $(A_1, ..., A_M)$  under the following constraints:  $P_1 \neq P_i \neq P_M$  where  $i \in (P_1, ..., P_M)$

 $P_i \in G(m_i, \sigma_i)$ 

• The output gives an identification probability for each mineral (several minerals can have non negative probability)

0.393188

0.761379

- 2. Improve the automatic EGO model parameter estimation
- 3. Take into account new noise model for completeness
- 4. Create database and associated expert rules
  - Adapt the procedure for mineral mixture
  - Develop expert rules for mineral characterization

.] R. Marion and V. Carrère, Mineral Mapping Using the Automatized Gaussian lodel (AGM) - Application to Two Industrial French Sites at Gardanne and Thann,	[6] J. M. Bioucas-Dias and J. M. P. Nascimento. Hyperspectral subspace identification. IEEE Transactions on Geoscience and Remote Sensing, 46(8) :2435–2445, Aug 2008.
emote Sensing 2018, 10, 146.	[7] P. Du, WA. Kibbe, SM. Lin, Improved peak detection in mass spectrum by
2] L. Pompilio, G. Pedrazzi, M. Sgavetti, E. Cloutis, M. Craig, and T. Roush.	incorporating continuous wavelet transform-based pattern matching. Bioinformatics,
xponential Gaussian approach for spectral modeling : the EGO algorithm I. band	2006.
aturation. Icarus, 2009.	[8] A. Tarantola, Inverse Problem Theory and Model Parameter Estimation. SIAM,
B] L. Pompilio, G. Pedrazzi, E. Cloutis, M. Craig, and T. Roush. Exponential gaussian	2005.
oproach for spectral modelling : the EGO algorithm II. band asymmetry. Icarus,	[9] J.P. Poli and L. Boudet, A fuzzy expert system architecture for data and event
010.	stream processing, Fuzzy Sets and Systems, 2018, 343, p.20-34.
]N. Clark, Roger & L. Roush, Ted., Reflectance Spectroscopy: Quantitative Analysis	[10] R.N. Clark, G.A. Swayze, R.A. Wise, K.E. Live, T.M. Hoefen, R.F. Kokaly and S.J.
echniques for Remote Sensing Applications. Journal of Geophysical Research	Sutley, 2007, USGS Digital Spectral Library splib06a: U.S. Geological Survey Data
tmospheres,1984.	Series 231
[] N. Acito, M. Diani, and G. Corsini. Signal-dependent noise modeling and model	[11] N. Zain, F. Van der Meer, H. Van der Werff, Effect of Grain Size and Mineral
arameter estimation in hyperspectral images. IEEE Transactions on Geoscience and	Mixing on Carbonate Absorption Features in the SWIR and TIR Wavelength Regions.
emote Sensing, 49(8) :2957–2971, Aug 2011.	Remote Sensing. 2012; 4(4):987-1003.