Massive analysis of multi-angular images by inverse regression of reflectance models

physical characterization of planetary surfaces.

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The Compact Reconnaissance Imaging Spectrometer for Mars

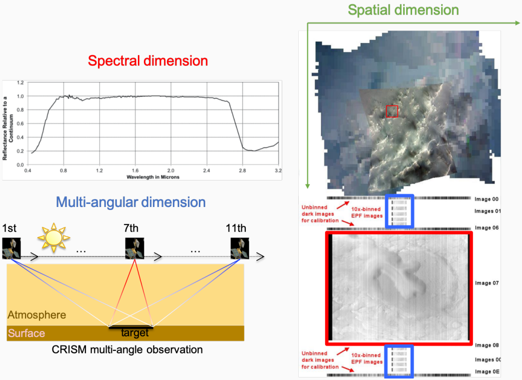
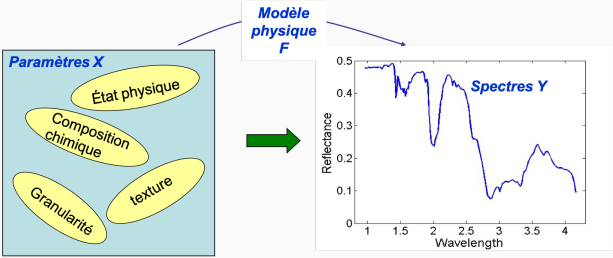


Figure 1: Acquisition of multi-angular hyperspectral image sequences by CRISM

- Multi-angular sequences of 11 hyperspectral images of planet Mars
- Image cubes : 11x11 km field of view; 600x600 spatial pixels; 360,000 spectra of 544 spectral bins.
- More than 8000 targeted observations acquired.

Physical models

- Different approaches are used to analyse the data and retrieve the information of interest.
- Inversion aims at determining the causes of a phenomenon from experimental observations of its effects.
- The resolution of such a problem generally starts by a physical model that theoretically describes how input parameters $x \in X$ are translated into observables $y \in Y$: *direct or forward* modelling of the phenomenon.
- Different kinds of physical models: analytical, numerical (ODEs, finite differences, etc.).



Goals and constraints of the analysis

The data can be decomposed into a series of vectors of observables Y_{obs} of dimension D.

Goal: from a vector Y_{obs}, estimating the mean or the most probable value for each of the L parameters [1] of the inverted physical model.

The method should address:

1. the large number of observations to be analysed and their large size,
2. the need to provide predictions for several correlated parameters,
3. the possibility of managing a possible multiplicity of solutions,
4. the requirement to accompany the latter with a quality measure (e.g. uncertainty).

[1] the components of vector X

Bayesian inversion by regression and sampling

Solving inversion problems (Tarantola, 2005) in a Bayesian framework usually requires the exploration of the posterior likelihood:

$$\phi = p(x|y) \propto p(y|X = x)p(x)$$

Regression strategy:

1. approximate the joint distribution:

$$p(X, Y) = (X, Y = F(X) + \epsilon)$$

with a parametric statistical model p_θ trained on a learning database $(X_n, F(X_n)),\ n = 1...N$ where X is uniform on parameters range, ϵ is a Gaussian noise.

2. for each Y_{obs}, compute the approximate posterior $p_\theta(X|Y)$ and use it to predict X.

Gaussian Locally-Linear Mapping (GLLiM)

The GLLiM model (Deleforge et al., 2015, 2014) is a parametric statistical model p_θ that:

- approximates the direct and inverse relationships between X and Y by a combination of K local affine transformations τ_k,
- provides approximations of both conditional probability distribution function (PDF) $p(x|y)$ and $p(y|x)$ as K -component Gaussian mixtures:

$$p(x|y) \approx p_{GLLiM}(x|y) = \sum_{k=1}^{K} w_k(y)\mathcal{N}(x; A_k y + b_k, \Sigma_k)$$

with $w_k(y) \propto \pi_k \mathcal{N}(y; c_k, \Gamma_k)$, $\pi_k = p(Z = k; \theta)$ the probability that X is the image of Y by the transformation τ_k $A_k \in \mathbb{R}^{L \times D}$ and $b_k \in \mathbb{R}^L$. Σ_k covariance of the error. K is estimated from the database using the Bayesian information criterion (BIC).

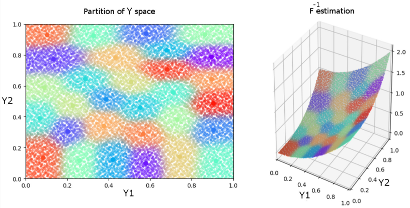


Figure 3: Left: partition of the Y space according to $p(Z = k|Y = y)$ Right: manifold $(Y_1, Y_2, \mathbb{E}[X|Y = y])$.

Planetgllim algorithm

- Planetgllim (Kugler et al., 2022) is a high-performance, documented, and open-source algorithm.
- It is optimised for the scientific cases where $D > L$, with typically $L < 10$, and D about few tens, while the number of observations to be inverted N_{obs} can be of the order of a few millions.

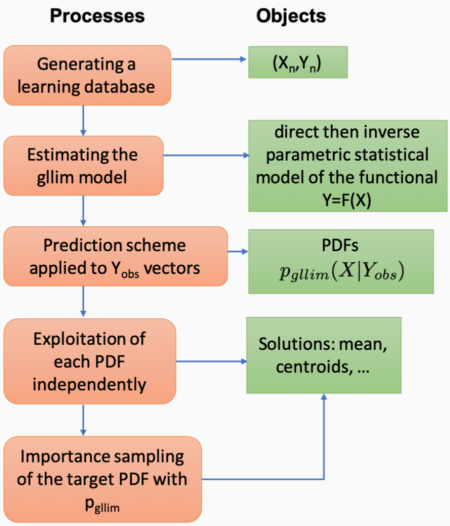


Figure 4: Workflow of planetgllim

Illustration: the Eos Chasma case

- Semi-circular depression in the Eos Chasma of Valles Marineris.
- Spectral signature of minerals :
  - hematite (Fe_2O_3),
  - kieserite ($MgSO_4.H_2O$) in high albedo sulfate-bearing material.

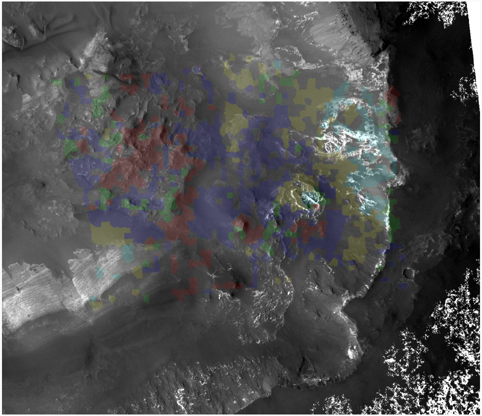


Figure 5: Classification map superimposed on a context image. The classification of the terrains is based on a kmeans clustering of their CRISM photometric curves at a wavelength of 755nm

Characterizing Mars surface by physical analysis

- Multi-angular sequences of CRISM images ($D \approx 11$, $N_{obs} \approx 5.10^5$).
- BRF models of granular media: Hapke and Shkuratov ($L = 4 - 6$).
- Parameters of interest: composition, granularity, micro-texture, and roughness of the surface materials (Fernando et al., 2016).

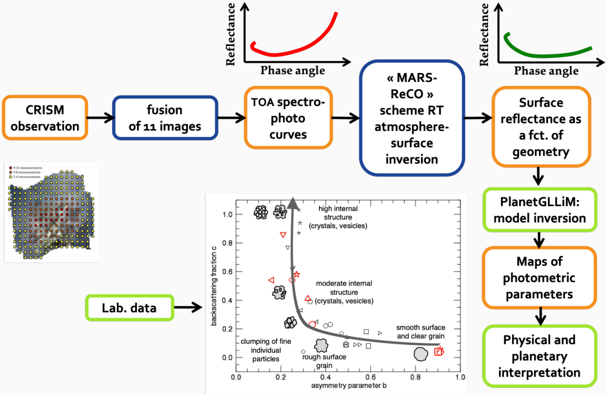


Figure 6: Pipeline for the analysis of a CRISM multi-angular image sequence.

Hapke model inversion

Hapke model massively inverted for 1648 pixels distributed across the scene and for 344 wavelengths between 0.44 and 2.60 microns (i.e. $N_{obs} = 566912$).

- spectrum of each Hapke parameter for different terrain classes.
- physical validity of the solutions.

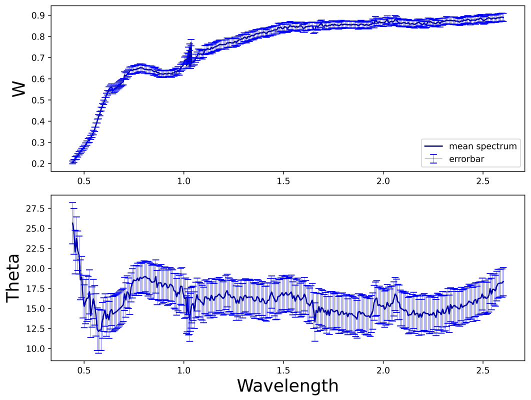
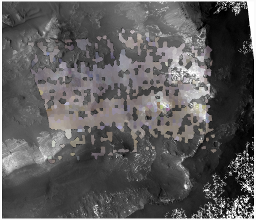


Figure 7: Spectral and spatial continuity of the Hapke parameters)



Micro-texture of the minerals

Comparison between the retrieved (b,c) parameters and that of reference materials measured in the laboratory.

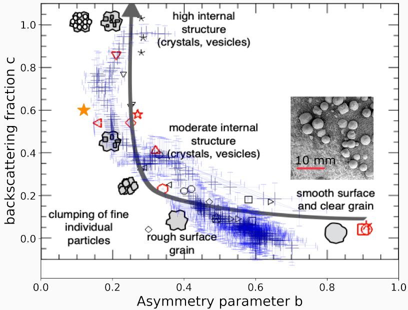


Figure 8: Spectral behavior of the phase function of the hematite bearing terrains. Moderately rough, rounded and clear grains can be inferred.

Inferred textures were actually observed by the Mars Exploration Rover Opportunity at the Martian surface for similar outcrops (inset):

- coarse-grained gray hematite,
- byproduct of the interaction of an acidic fluid with basaltic rocks,
- found near sulfate-rich sedimentary materials.

Conclusions

- **PlanetGLLiM is a software for the physical analysis of multi-dimensional data in planetary remote sensing**:
  - based on **the Gaussian Locally-Linear Mapping method**.
  - specifically tailored to handle inversion of bidirectional reflectance models given sets of multi-angular measurements.
  - efficient processing of multi-angular sequences of hyperspectral images of planet Mars.
- Planetgllim is distributed as open software on gitlab INRIA under CECILL licences.
- Planetgllim can be **adapted to similar inversion problems for massive data analysis.**

Thank you

References

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