

Estimation of surface photometric parameters: Bayesian inversion on Hapke's model

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Abstract

Bayesian inversion is a powerful approach for the inversion of the non-linear Hapke's model in order to estimate surface photometric parameters. This technique is based on the concept of the state of information, characterized by a probability density function (PDF). The prior information on model parameters combined with prior information on observations are fused to infer the solution. The final state of information is numerically sampled using a Monte Carlo Markov Chain, allowing rigorous estimation of uncertainties.

1. Introduction

Fast and accurate direct models describing the interaction of light with dense granular medium (e.g. planetary surface) are required to derive compositional and structural informations (i.e. grain size, shape, internal heterogeneity, surface compaction, roughness) from reflectance measurements of the planetary surface (Bidirectional Reflectance Function or BRF). Due to its fast computing, Hapke's model [1] appears the best candidate to analyze surface BRF. We implemented and tested a Bayesian inversion to analyze synthetic datasets and the 11 multi-angle CRISM data of Mars [2] after aerosols correction using the Multi-angle approach for retrieval of surface reflectance from CRISM observations technique (MARS-ReCO) [3].

2. Hapke's photometric model

The Hapke's model [1] is widely used in the planetary community depending on 6 parameters: single scattering albedo ω , macroscopic roughness θ -bar, particle phase function which is described by a 2-term Henyey-Greenstein function that includes the asymmetric parameter b and the backscattering fraction c , and opposition effect described by its width h and magnitude B_0 .

3. Bayesian inversion framework

Inversion problems do not have a unique solution if the direct model is nonlinear as does the Hapke's model. Tarantola and Valette [4] proposed to solve inverse problems in a general nonlinear case based on the concept of the state of information using Baye's theorem. The key points of the Bayesian inversion framework are:

- *Prior information on the model.* The prior information on model parameter in the parameter space $p(m)$ is independent with the data and corresponds in our case in all physically possible values. For all 6 parameters, we consider a uniform PDF on an interval that insures their physical relevance (from 0 to 1 for ω , b , c , B_0 and h and from 0° to 45° for θ -bar).
- *Prior information on the data.* The prior information on data in the observation space $p(d)$ is assumed to be a Gaussian PDF. Each observation value at one geometry i , is accompanied with its standard deviation σ_i assumed to be independent on the other geometries. The Gaussian PDF is described by a diagonal covariance matrix C with elements $\sigma_1^2, \dots, \sigma_N^2$, N is the number of geometries. For Mars, this information is provided by MARS-ReCO on real CRISM observation [3].
- *Posterior PDF of each parameter.* Inversion problems correspond to the particular case where information from the data space is translated into the model space. Assuming an uniform null information state, the posterior PDF $P(m)$ in the model space is [4]: $P(m)=k.p(m).L(m)$, (1) where k is an appropriate normalization constant, $L(m)$ is the «likelihood function» which measures the fit between observed and modeled data and We suppose a Gaussian uncertainties described by a covariance matrix C , then:

$$L(m)=k.exp[-0.5.(d_{mod}-d_{mes}).C^{-1}.(d_{mod}-d_{mes})]$$
 (2)
- *Sampling of solutions.* It is not possible to analytically describe the posterior PDF because the Hapke's model is nonlinear. Consequently, it is sampled by randomly generate a large collection of model parameters according the posterior PDF and the relative likelihood (Monte Carlo Markov Chain)

[6]. The best trade-off between computation time and accuracy is a burn-in phase of 500 runs. The next 500 runs are used to create the posterior PDF.

4. Sensitivity study

The capabilities of the proposed inversion strategy have been tested on synthetic data that mimic reflectance measurements at different viewing geometries. A realistic synthetic data set is simulated using in situ photometric parameters of soils on Mars estimated from reflectances measured by the Pancam instrument on-board Mars Exploration Rover (MER) [5] at ~ 750 nm. The synthetic data is simulated: (case 1) for a reduced geometric configurations close to the CRISM acquisition: 11 multi-angle hyperspectral images (constant incidence angle, 11 different emission angles ($\pm 60^\circ$) and 2 azimuthal angles) [2], and (case 2) for varied and diverse geometric configurations (varied incidence, same emergence and azimuth angles). For the case 1, the parameter ω has a Gaussian distribution with a lowest standard deviation. It is the best-constrained parameter in photometric modeling. The parameters c , and $\theta\text{-bar}$ are less constrained than the parameter ω (asymmetric, bimodal distributions and high standard deviations). The parameter b has no solution (uniform PDF close to the prior PDF). The reason is that for a single CRISM observation, the geometries are not varied enough to well-constrained these 3 parameters. For the case 2, results show that all the parameters have a constrained solution and the a posteriori PDF are Gaussian-like distributions with lower standard deviation. The mean of each photometric parameters are close to the initial parameters. This study shows the importance to improve the number of geometries, by combining more overlapping strips at different times along the

mission to complete as possible the whole phase function.

5. Conclusions

Bayesian inversion is a useful approach to invert the non-linear Hapke's model for the estimation of surface photometric parameters. Thanks to Bayesian inversion, the shape of the a posteriori PDF is known and will inform us whether the BRF sampling is sufficient to estimate accurate photometric parameters. From our synthetic tests, a lack of the BRF sampling produce a uniform non-constrained PDF or multimodal PDF. An application of this method on CRISM multi-angle observations at MER landing sites is presented by J. Fernando et al. [7,8].

References

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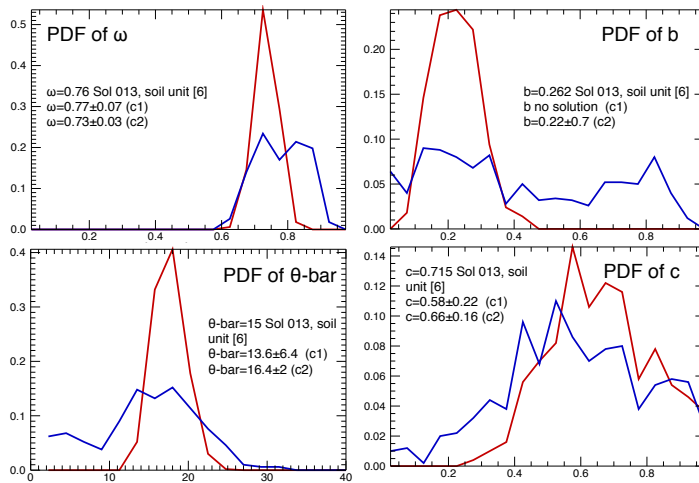


Figure 1: A posteriori PDF and mean and standard deviation of the parameters ω , b , c , $\theta\text{-bar}$ for the case 1 in blue line (inc= -60° , eme=from -60° to 0 and from 0 to $+60^\circ$, phi=[$60;120^\circ$], geometries=11), and for the case 2 in red line (inc=[$30-80$], $\Delta=10^\circ$ eme=[$0-70^\circ$], $\Delta=20^\circ$ phi=[$60;120^\circ$], geometries=60)