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Corrections of the PFS/MEx perturbations

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Abstract

The Planetary Fourier Spectrometer (PFS) instrument on board the Mars Express mission generated a large database of spectral information for the Red Planet from the start of its mission. The objective of this work is to correct major limitations of the instrument caused by micro-vibrations which generate "ghosts" in the acquired spectra. The observed spectra can be seen as a convolution between the original clean Martian spectra and perturbation kernels. A blind deconvolution approach in the field of inverse problems is used to remove the ghosts from the measured Martian spectra through an Alternating Minimization algorithm (AM). Constraints are applied so that the estimates respect the physical properties of the investigated signals.

1. Introduction

The ghost problem of the Mars spectra was first analyzed in [4]. In [6] and [5] a precursor methodology of the one proposed here was presented. First, the analytical model was developed to justify the first-order approximation by convolution [6]. There are three sources for Mars spectrum ghosts: the sampling step error and the cyclic misalignment of the cubic corner mirrors of the interferometer, both due to micro-vibrations caused by other instruments on board the mission satellite and the asymmetry error of the interferogram due to the random start of the acquisition. By mathematically modeling these errors and inserting them into the definition of a monochromatic source, we have observed that these errors are represented by Diracs at specific frequencies and have a harmonic propagation behavior inside the Mars spectra. Therefore the kernel must be estimated with a sparsity inducing algorithm that can handle complex values.

Based on that work, a first attempt of blind deconvolution was proposed [5]. Typical results of this strategy are shown in fig. 1. The averaged spectrum shows a pronounced smooth aspect indicating that an algorithm to estimate one Mars spectrum should be able to deliver smooth solutions that additionally are real and positive.

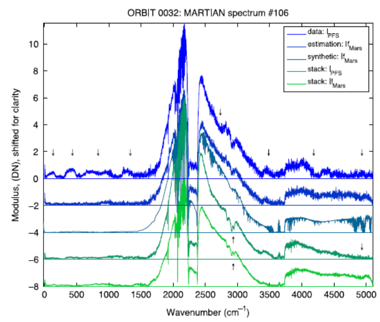

Figure 1: In Figure 1 the first spectrum from above is the measured spectrum from the PFS containing ghosts marked by arrows. The second spectrum is the result from [5] while the third is a synthetic simulation. The last two are an average of 11 non-treated spectra and an average of 11 estimated spectra with [5] respectively.

2. Methodology

2.1. Direct problem

$$m * k = s \quad (1)$$

Where: $\mathbf{s} \in \mathbb{C}$ is the measured spectrum, $\mathbf{k} \in \mathbb{C}$ is the perturbation kernel, $\mathbf{m} \in \mathbb{R}$ is the original Mars spectrum, $*$ is the convolution.

2.2. Inverse problem

$$||s - m * k||_2^2 + \lambda_m ||Dm||_2^2 + \lambda_k ||k||_1 \quad (2)$$

Where: $||s - m * k||_2^2$ is the fidelity to the data term, $\lambda_m ||Dm||_2^2$ is a smoothing regularization term and $\lambda_k ||k||_1$ is a sparsity inducing regularization term. This expression is non-convex but does become convex if one of the regularization terms is fixed.

2.3. AM Algorithm

To estimate **m**, we use an AM algorithm with two alternating steps: to estimate Mars a projected Newton algorithm [2] is used in the first step while the kernel is considered known, then to estimate the kernel a FISTA algorithm [1] is used while the Mars signal is considered known:

Initialize $m_0, k_0, \alpha_{m_0}, J_{old} = 0, \hat{s} = m_0 * k_0$

$J_i = ||s - \hat{s}||_2^2$

While $|J_{old} - J_i| > \epsilon_{stop}$

1. $\Delta_{n_i} = (M_{i-1}^T M_{i-1} + \lambda_{m_i} D^T D)^{-1} \cdot M_{i-1}^T \hat{s}$
   $m_i = P((1 - \alpha_{m_i}) \cdot m_{i-1} + \alpha_{m_i} \cdot \Delta_{n_i})$
   update α_{m_i}, choose best λ_{m_i} from given range
2. $k_i = P\left(\underset{k}{prox}\left(k_{i-1} + \frac{\lambda_{k_i}}{L} m_i^*(s - m_i * k_{i-1})\right)\right)$
   choose best λ_{k_i} from given range
3. check stopping criterion:
   $J_{old} = J_i, \hat{s} = m_i * k_i$
   $J_i = ||s - \hat{s}||_2^2 + \lambda_{m_i} ||Dm_i||_2^2 + \lambda_{k_i} ||k_i||_1$

End While

Where: Δ_{n_i} and α_{m_i} are the Newton's step and step size, J_i is the functional value at each iteration, P is the projection on the constraints given, $prox$ is the proximal of k_i onto a convex subset [3], L is the Lipschitz constant.

3. Results and Conclusions

In Figure 2 the same spectrum from the same orbit as in [5] is presented: the measured spectrum, the result from [5] and the result from our AM algorithm. Mars-AM shows a smoother estimated spectrum, with an attenuation of the ghosts and preservation of the absorption bands. Regarding the AM algorithm itself there are three major improvements: automated choice of λ_m and λ_k hyper-parameters at run time with different strategies, the algorithm allows constraints to be applied on the estimated signals (real valued, positivity) and the addition of an automatic stopping criterion for the estimation. This new strategy opens new perspectives on the correction of the full PFS dataset.

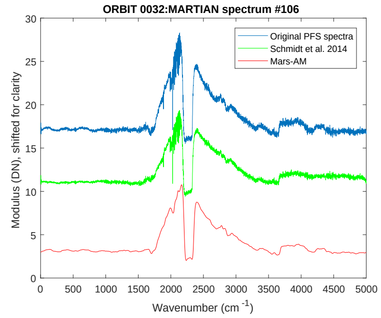

Figure 2: Preliminary results of our new approach. (i) PFS measured spectrum, (ii) Previous results from [5], (iii) Our AM algorithm.

Acknowledgements

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