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Accuracy and performance of linear unmixing techniques for detecting minerals on OMEGA/MEx

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Abstract

Detecting minerals on a huge hyperspectral dataset (> To) is a difficult task that we proposed to address using linear unmixing techniques. We test different algorithms with positivity constrains on a typical Martian hyperspectral image of the Syrtis Major volcanic complex. The usefulness of additional constraints, such as sparsity and sum-to-one constrains are discussed. We compare the results with a supervised detection technique based on band ratio.

1. Introduction

In remote sensing hyperspectral imaging, a set of images is recorded at various spectral bands by the sensor which measures the solar light reflected and scattered back from the surface and from the atmosphere. Under some assumptions related to surface and atmosphere properties - i.e., Lambertian surface, no intimate mixture, no diffusion terms in the atmosphere, and homogeneous geometry in the scene - each measured spectrum X (each pixel of the observed image for several spectral bands) can be modeled as a linear mixture of the scene component spectra (endmembers).

$$\mathbf{X} \approx \mathbf{AS} \qquad (1)$$

In this model, the weight A of each component spectrum S is related to its abundance in the surface area corresponding to the underlying pixel. Supervised linear unmixing problem consists of estimating matrix A knowing X and S, in contrary to unsupervised unmixing that consists of estimating matrix A and S, knowing only X [1]. A first strong constraint is the non-negativity of the elements of A since they correspond to abundances of the surface components:

$$A_{p,r} \geq 0, \forall p,r \qquad (2)$$

A second constraint that may be imposed is the sum-to-one (additivity) constraint on the abundances that should sum to unity for each pixel p:

$$\Sigma_r A_{p,r}=1, \forall p \qquad (3)$$

A third constraint that may be imposed is the sparsity of A, meaning that only a few spectra in the reference spectral library contribute to each observed spectrum. That is, most abundances $A_{p,r}$ should be equal to zero. We consider the Basis Pursuit De Noising approach to this problem, which consists in minimizing the least-squares criterion related to (1), penalized by the L1-norm of the coefficients:

$$\min \Sigma_r |a_{p,r}|, \forall p \qquad (4)$$

2. Results

We use the OMEGA hyperspectral detector because of its high signal-to-noise ratio. We select the observation ORB0422_4 of Syrtis Major as a test case because this single cube contains well identified areas with very strong signatures of mafic minerals (orthopyroxene, clinopyroxene, olivine) and phyllosilicates. We use 109 wavelengths within the 128 original wavelengths of the C channel. The cube has been radiometrically corrected and the atmospheric gas transmission has been empirically corrected using the volcano scan method.

The band ratio methods and bands depth estimation are commonly used to detect minerals on OMEGA data [2]. Unfortunately, this method is valid only if at least two wavelength channels can be identified as affected by only one particular mineral.

The Iterative Linear Spectral Unmixing Model (ILSUM) is based on a Least squares inversion of equation 1 performed iteratively [3]. The endmember with the most negative coefficient found during the first inversion process is eliminated from the input library and the inversion is performed again with the new cleaned library. This process is repeated until no negative coefficient is found.

The FCLS method solves the unmixing problem under non-negativity and sum-to-one constraints [4]. Since no closed form expression of the optimal abundance vector can be derived under these two constraints, an iterative scheme is developed. The non-negativity constraint is classically handled by introducing the Lagrange function associated with the criterion to be optimized. The sum-to-one constraint is considered as an additional measurement equation leading to a new cost function. This method was previously tested to detect ices and liquid water on Mars [5]

The Fully Constraint-Scale Gradient Method (FC-SGM) has been proposed in [6] as an alternative of FCLS to solve the linear unmixing problem under the non-negativity and sum-to-one constrains using the scaled gradient method The criterion to be optimized is derived from the Lagrangian formulation including the non-negativity constraint. Then this criterion is minimized thanks to an iterative scaled gradient method. The sum-to-one constraint is conveniently ensured by projecting the abundance vector onto the appropriate subspace at each iteration of the algorithm.

We consider the Basis Pursuit De Noising (BPDN) approach [7] that solves the unmixing problem under the sparse constraint on matrix A. Sparsity is achieved by minimizing the least-squares term corresponding to (1), penalized by the L1 norm of the coefficients. A regularization parameter has to be tuned, which controls the trade-off between both terms. It is somehow related to the degree of sparsity of the solution. In the following, it was fixed to 1.

3. Discussions and Conclusion

In the problem with a collection of 33 reference spectra and 109 wavelengths (fig. 1), the sparsity constraint from the BPDN method seems to be useless since the results are similar for ILSUM (without sparsity), FCLS (without sparsity) and BPDN (with sparsity). In future studies, much larger reference catalogues must be considered but, from a prior study, neither ILSUM nor FCLS seems to be well suited to this situation. The behavior of FC-SGM and BPDN would be studied in this situation. Thanks to these results and the fast computation time of ILSUM and FCLS linear unmixing methods, they can be applied on large scale datasets (such as the complete OMEGA archive) in order to detect automatically the minerals at the surface on Mars [13]. The application of FC-SGM and BPDN would require an optimized implementation.

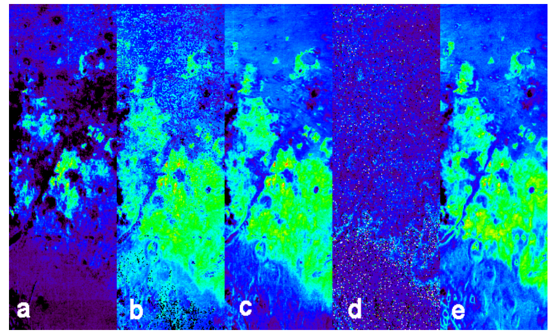

Fig 1. Image of the detection of orthopyroxene (opx). (a) reference band ratio, (b) abundance estimated abundance estimated with ILSUM, (c) with FCLS, (d) with FC-SGM, (e) with BPDN.

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