MATERIAL IDENTIFICATION ON MARTIAN HYPERSPECTRAL IMAGES USING BAYESIAN SOURCE SEPARATION

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ABSTRACT

Identification of materials in a planetological scene observed by an imaging spectrometer is a common problem in remote sensing. Usually the pixel size is larger than the typical size of material change over planets, leading to a linear spatial mixing. We propose here an unsupervised approach based on source separation methods to estimate the pure spectra of the components present in the observed scene and their abundances in each pixel. Previous studies have shown that this approach is interesting for Martian ices [1]. This method assumes the positivity of both the pure spectra and the mixing coefficients. We propose here to apply this technique to detect Martian minerals and we show that adding the sum-to-one constraint (or additivity constraint) on the abundance vectors allows one to improve the estimation performance.

***Index Terms*—** Hyperspectral, unsupervised classification, Bayesian blind source separation, independent component analysis, Mars.

1. INTRODUCTION

The OMEGA [2] instrument is a imaging spectrometer on board Mars Express (European Space Agency), which provides hyperspectral images of the Mars surface, with a spatial resolution from 300m to 4km, 256 frequency channels in the near infra-red and 128 channels in the visible range. This high spatial and spectral resolution, and its wide spectral range, give the ability to detect chemical species on the surface and the atmosphere of Mars more accurately than before.

The signal recorded by the instrument is the solar light reflected and diffused back by the planet surface and atmosphere. Under some assumptions related to the surface composition and the light incidence [1], the measured signal can be modeled as a linear mixture of pure spectra. In this model the weight of each pure spectrum can be linked to the its abundance in the surface. In this study, we empirically correct the atmosphere absorption [3] such that the mixing coefficient will correspond to abundances. In such situation, the hyperspectral data processing algorithm should take into account the sum-to-one constraint of the abundances in addition to the positivity of the abundances and the pure spectra. Recently, we proposed two source separation algorithms that allows one to satisfy these constraints within a hierarchical Bayesian model (see [4] and [5, 6]. As the estimation procedure is conducted using Markov chain Monte Carlo (MCMC) methods, a pixel selection step is also introduced to reduce the computation complexity of the algorithm [1]. In this paper, we apply these algorithms to real hyperspectral data and show that adding the sum-to-one constraint leads to an improvement of the hyperspectral data analysis.

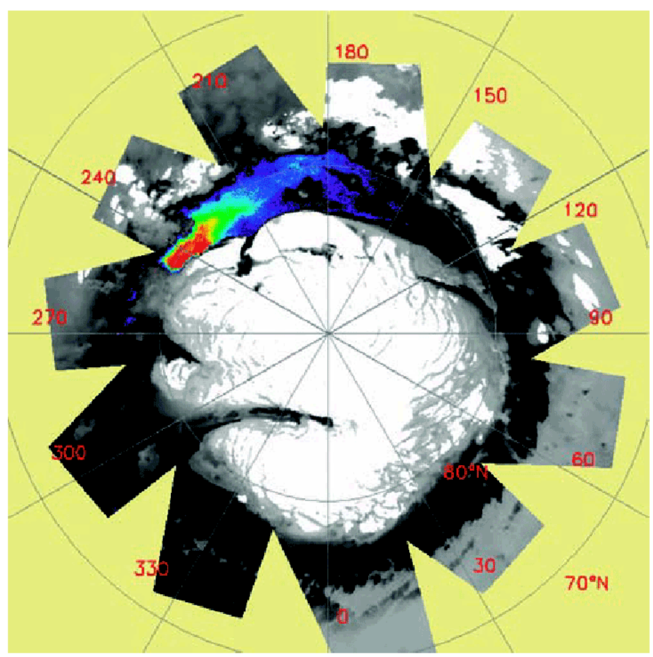

Fig. 1. Map of detected sulphate from [7].

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2. DATASET

The algorithms have been applied on a particular Martian terrain in the polar Northern plains observed during the local summer, where sulphates (mainly gypsum) have been recently detected [7]. This mineral type is interesting because it could sign the presence of liquid water that has some implications on the Red Planet evolution. Because there is no ground truth, we propose to consider the map based on a supervised detection method using band ratio [7] as a reference map of surface proportion (Fig. 1).

The gypsum spectral reference recorded in the Laboratoire de Planétologie de Grenoble by A. Pommerol (Fig. 4) has been also used. We produce a mosaic made of 8 OMEGA images georeferenced in stereographic north polar projection: ORB0972-2, ORB0973-2, ORB0975-2, ORB0976-2, ORB0979-2, ORB0980-2, ORB0989-2, ORB1004-2. We choose 107 spectral bands with reduced noise level, reduced atmospherical residue in the spectral domain from 1 to 2.5 microns (C detector of OMEGA instrument). Water ice, with strong absorption bands compared to gypsum, is present in this season on the polar cap. In order to focus on minerals detection, we propose to filter all ice spectra on the scene using the WAVANGLET method [8].

3. MODEL AND METHODS

By considering P pixels of an hyperspectral image acquired at L frequency bands, the observed spectra are gathered in a $P \times L$ data matrix $\mathbf{Y}$. Each row of this matrix contains the measured spectrum at each pixel with spatial index $p = 1, \ldots, P$. According to the linear mixing model, the pth spectrum can be expressed as a linear combination of the R pure spectra of the surface components. Using matrix notations, this model can be written as

$$\mathbf{Y} \approx \mathbf{AS}. \tag{1}$$

The rows of matrix $\mathbf{S}$ contain the pure spectra of the R components and each element A_{pr} of matrix $\mathbf{A}$ corresponds to the abundance of the rth component in pixel with spatial index p. For a qualitative and quantitative description of the observed scene composition, we propose to estimate the matrices $\mathbf{A}$ and $\mathbf{S}$ to explain the data matrix $\mathbf{Y}$ with a physical interpretation. In this respect, a hard constraint is the positivity of the elements of both matrices $\mathbf{S}$ and $\mathbf{A}$ since they correspond to spectrum amplitudes and abundances, respectively. A second constraint that may be imposed is the additivity constraint. Indeed the abundance coefficients correspond to proportions and therefore should sum to unity. This constrained estimation task can be viewed as a source separation problem and can be addressed in a Bayesian framework. We recently proposed two algorithms to perform an unsupervised joint estimation under positivity constraints (BPSS1) [4] and also to include the additivity constraint (BPSS2) [5, 6]. These two algorithms are based on hierarchical Bayesian models to encode prior information regarding the parameters of interest and include the additivity and sum-to-one constraints. The complexity of the resulting posterior distribution is overcome by using MCMC methods. The algorithms details are not described here, and the interested reader is invited to consult the works [4] and [5, 6] for further details.

However, since these algorithms use MCMC methods, the computation time increases with the image size. We thus proposed in [1] a method that allows to combine independent component analysis (ICA) using JADE algorithm [9] and Bayesian positive source separation (BPSS). ICA allows one to get a rough spatial classification of the scene and therefore to select a few but relevant pixels (i.e., from each "class", we select the pixels whose spectra are mostly uncorrelated). Those pixels will serve in the Bayesian separation algorithm to estimate the component spectra.

4. RESULTS AND DISCUSSION

4.1. Separation under positivity constraint

The results of the separation using positivity constraint alone are presented in Fig. 2. Several numbers of sources have been tested without significant improvement. Consequently, only the results obtained for 3 sources are depicted here. The selection of pixels has been performed on 8 independent components determined by the JADE algorithm (filtering of 2 components obviously noisy selected by the user) using 10 spectra selected for each component. The total lack of fit is 0.89.

The pure spectra and the map of surface proportion are represented in Fig. 2. Although the estimated surface proportion of the third source (on right) reveals a pattern that could be compatible with the previous detection [7] (see Fig. 1), none of the spectral sources can be easily identified to gypsum. This result can be interpreted as a lack of constraint of the BPSS1 algorithm and possibly to an interference due to the presence of a limited number of water ice spectra with strong absorption bands.

4.2. Separation under positivity and additivity constraints

The results of the separation after adding the additivity constraint (BPSS2) are depicted in Fig. 3. Similarly, the results obtained for 3 sources are presented. The selection of pixel has been performed on 10 independent components identified by the JADE algorithm (without noise filtering) with 10 spectra selected for each component. The total lack of fit is 6.6. The first two sources are not directly interpretable and should be attributed to the effect of water ice trace with strong absorption bands. Interestingly, the last source is compatible with the reference dataset for the spectra and the map (see section 2). Characteristic absorption bands at 1.5 microns and 1.95 microns are well detected and the spatial pattern is compatible with the supervised method [7]. Fig. 4 exhibits the

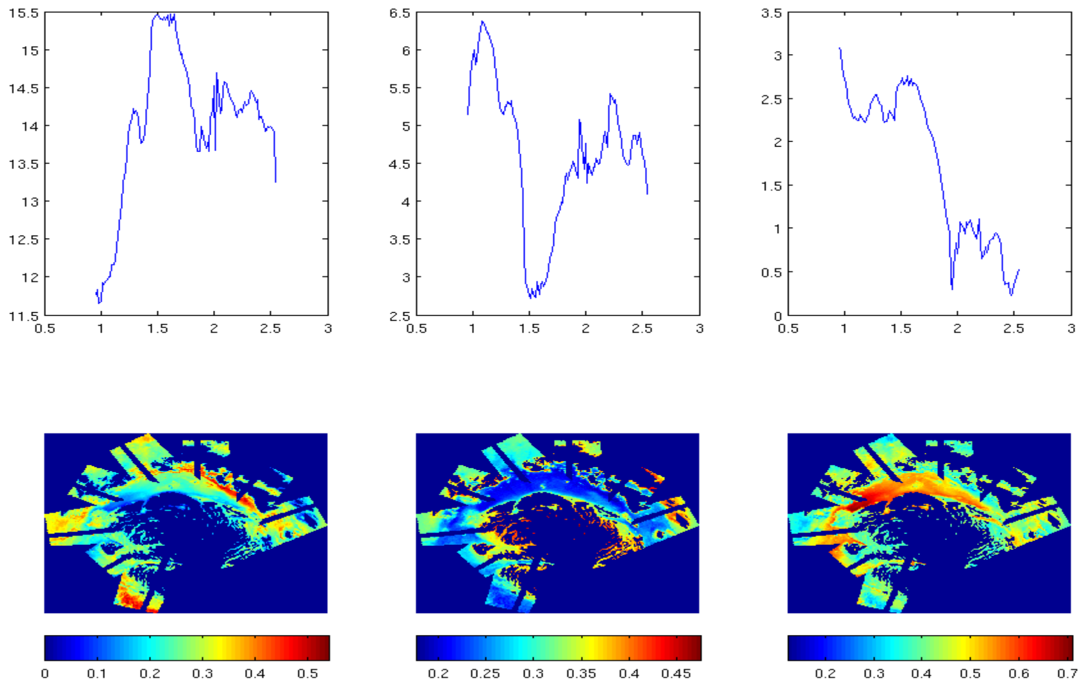

Fig. 2. Results of the separation under positivity constraint only (BPSS1): estimated material spectra (top) and corresponding abundance maps (bottom) represented in color from blue (0) to red (maximum).

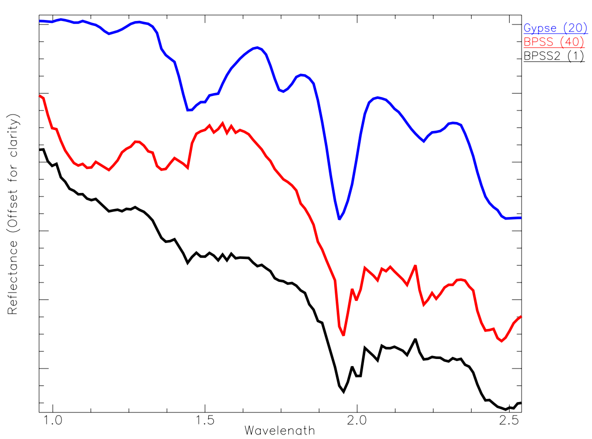

Fig. 4. Spectra estimated by the positivity only (BPSS1, red), positivity and additivity (BPSS2, black) and the laboratory spectra of gypsum (blue). For clarity, all spectra have been scaled with a the factor indicated on the legend.

two spectra estimated by BPSS1 and BPSS2 (third source for each) and the gypsum measured in laboratory. There is a bad match between the BPSS1 and the reference spectra at 1.1 microns and 1.75 microns. Those two spectral region are significantly better estimated with the BPSS2 method. The correlation coefficient significantly improve from 0.87 to 0.93.

5. CONCLUSION

We showed that the detection of minerals present at the surface of Mars using hyperspectral imaging and source separation is a relevant approach. In previous work, we demonstrated that the positivity constraint is required to interpret the result in physical term in an example based on Martian ice [1]. In the present work, focused on mineralogy in the Northern plain of Mars, we show that the sum-to-one constraint significantly improves the detection of surface minerals. We infer that the relative weak absorption bands of minerals compared to ice is the main reason to this behavior. In future works, we will apply the separation algorithm with positivity and additivity constraints on other hyperspectral dataset.

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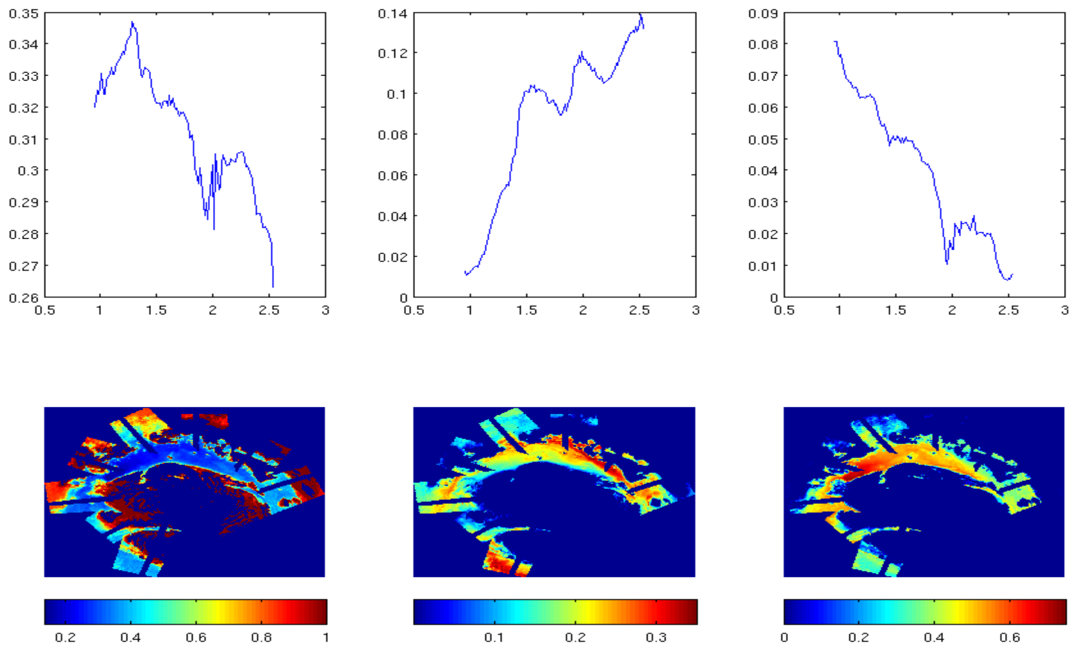

Fig. 3. Results of the separation under additivity and positivity constraints: estimated material spectra (top) and corresponding abundance maps (bottom).

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