Mars Hyperspectral Data Analysis using ICA and Bayesian Positive Source Separation

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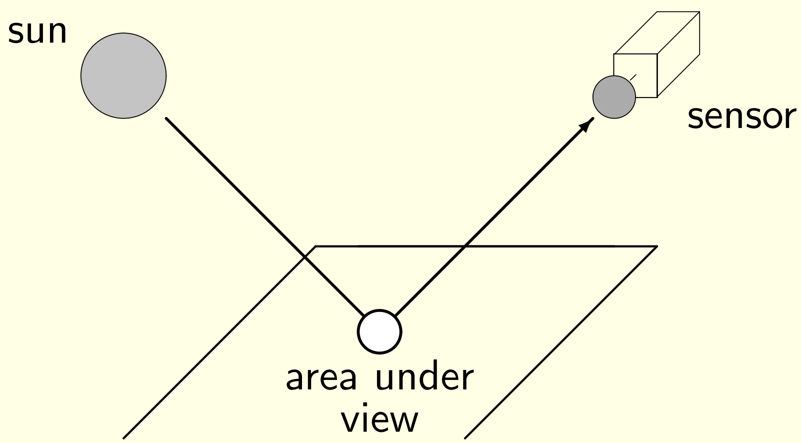
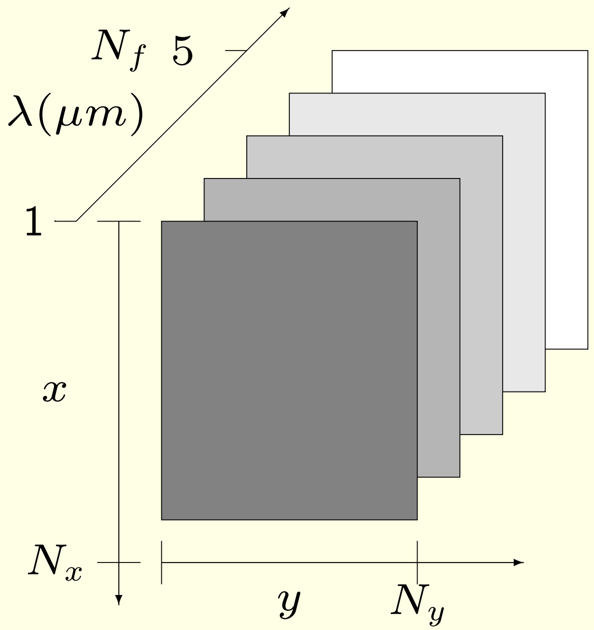
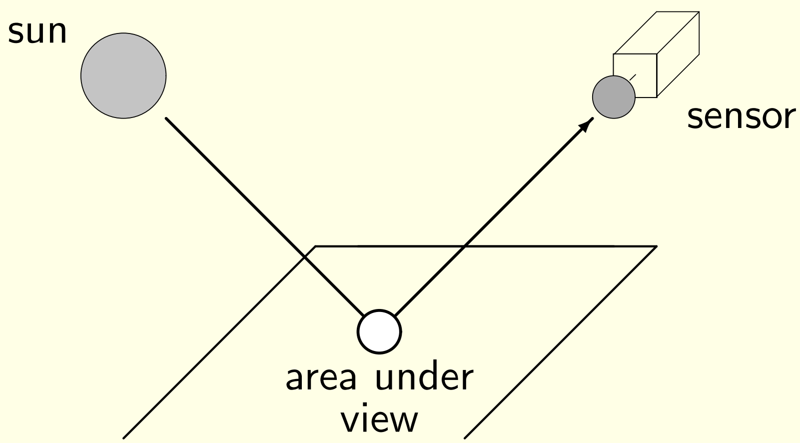
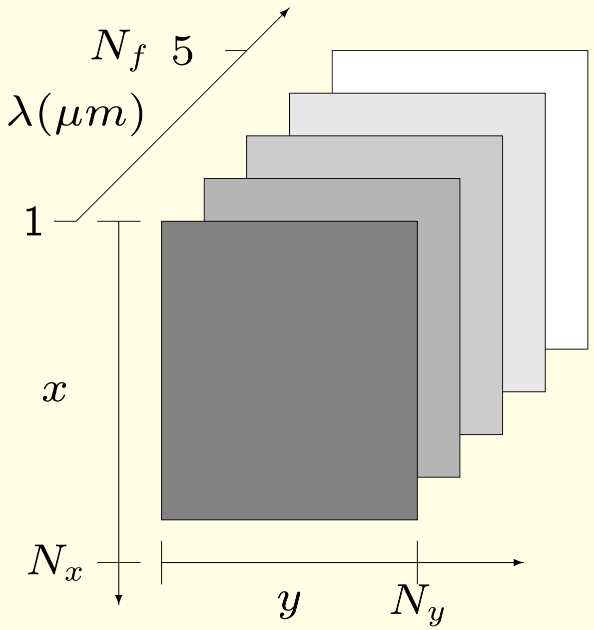
Hyperspectral Imaging and Planetary Surface Analysis





Hyperspectral Imaging and Planetary Surface Analysis





⊛ Mars Express Mission: OMEGA spectro-imaging instrument

- cubes of 256 spectels, 256 lines and 2000 columns $\Rightarrow$ more than 500 000 pixels,
- spatial resolution: $\sim$ 1 km,
- spectral resolution: $\sim$ 100 nm.

Outline

1. **Observation model**
2. **Mixture models**
3. **Proposed approach and experimental results**
4. **Conclusions**

1. Observation model

1.1 Geographical Mixture

$$L(x,y,\lambda) = \Phi(\lambda)\left(L_a(\lambda) + \sum_{p=1}^{P} \alpha_p(x,y)\, L_p(\lambda)\right)\cos\left[\theta(x,y)\right]$$

- $L(x,y,\lambda)$: radiation measured by the sensor,
- $\Phi(\lambda)$: spectral atmospheric attenuation,
- $\theta(x,y)$: angle between the sunlight incidence vector and the surface normal,
- P: number of constituents,
- $L_p(\lambda)$: reflectance of the p-th constituent,
- $\alpha_p(x,y)$: weight of the p-th constituent,

$$L(x,y,\lambda) = \sum_{p=1}^{P} \alpha'_p(x,y)\, L'_p(\lambda) + E(x,y,\lambda),$$

- $\alpha'_p(x,y) = \alpha_p(x,y) \cos\left[\theta(x,y)\right] \longrightarrow$ geometrical effect.
- $L'_p(\lambda) = \Phi(\lambda)\, L_p(\lambda),$
- $E(x,y,\lambda) = \Phi(\lambda)\, L_a(\lambda) \cos\left[\theta(x,y)\right].$

– Geometrical effect: handled when estimating the abundances fractions

$$c_p(x,y) = \frac{\alpha'_p(x,y)}{\sum_{j=1}^{N_c} \alpha'_j(x,y)} = \frac{\alpha_p(x,y)\cos[\theta(x,y)]}{\sum_{j=1}^{N_c} \alpha_j(x,y)\cos[\theta(x,y)]} = \frac{\alpha_p(x,y)}{\sum_{j=1}^{N_c} \alpha_j(x,y)}.$$

– Atmospheric attenuation: inherent in the spectra

1.2 Data approximation models

⊛ **Spectral mixing:** each pixel of spatial index $n = (x, y)$ gives a spectrum of N_f frequency samples

$$I_n(\lambda_k) \approx \sum_{p=1}^{N_c} a_{(p,n)} \psi_p(\lambda_k), \quad \forall n = 1, ..., N_x \times N_y,$$

which leads to

$$\mathbf{I}(\lambda_k) \approx \mathbf{A} \cdot \Psi(\lambda_k).$$

⊛ **Spatial mixing:** for each wavelength λ_k, the measured image $I_{\lambda_k}(n)$ is a weighted sum of N_c basis images

$$I_{\lambda_k}(n) \approx \sum_{p=1}^{N_c} b_{(\lambda_k,p)} II_p(n), \quad \forall k = 1, ..., N_f,$$

which leads to

$$\mathbf{I}(n) \approx \mathbf{B} \cdot \mathbf{II}(n).$$

2. Separation using ICA and BPSS

2.1 Problem Statement

- independence assumption is not satisfied by the spatial/spectral sources,
- fast but leads negative components,
- positivity constraint can be ensured in a Bayesian source separation approach,
- requires MCMC methods: high computation cost due to the huge number of spectral mixtures (pixels).

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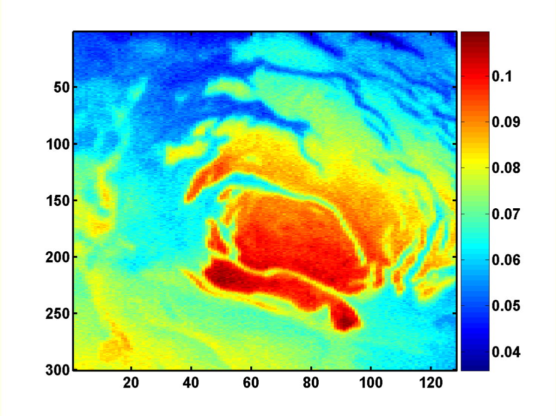
2.2 Proposed Approach

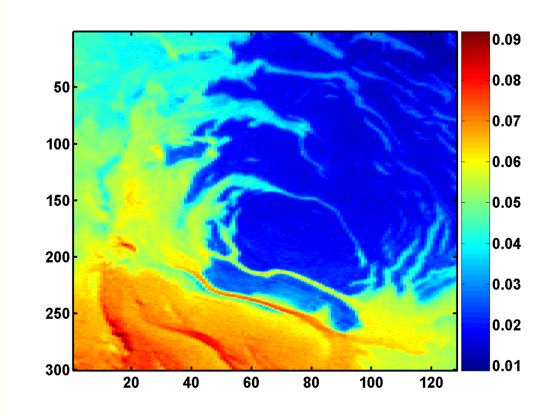
1. Spatial independent component analysis using JADE,
2. Selection of few relevant pixels using the ICA results,
3. Spectral Bayesian source separation with positivity constraint.

2.3 Illustration with a Benchmark data set

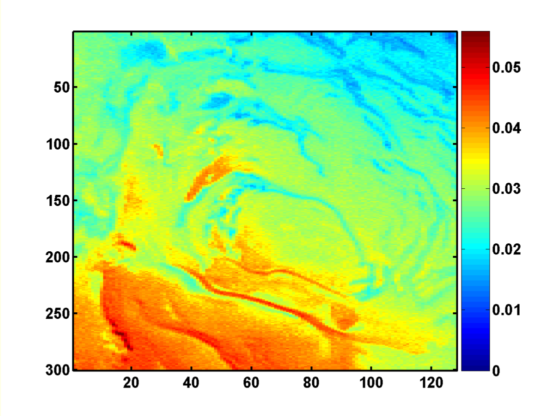
⊛ **Data :** south polar cap of Mars. 300 lines, 128 columns and 184 spectels.



(a) $\lambda = 0.95\mu m$



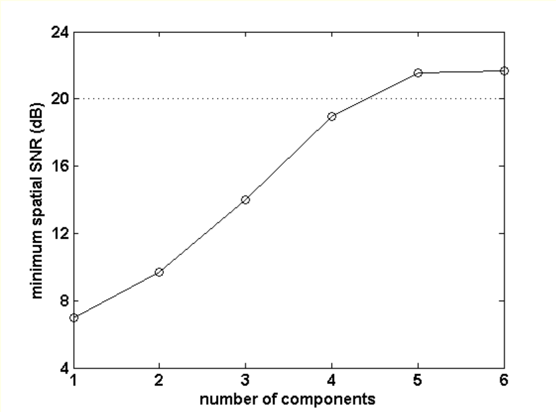
(b) $\lambda = 2.61\mu m$



(c) $\lambda = 3.45\mu m$

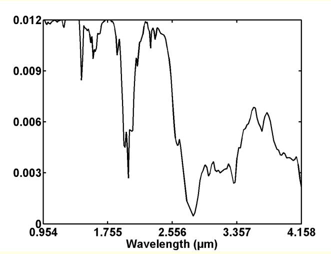
⊛ Spatial independent component analysis (with JADE)

$$SNR(n) = 10\log_{10}\left(\frac{\sum_{k=1}^{N_f} I_{\lambda_k}(n)^2}{\sum_{k=1}^{N_f}\left(I_{\lambda_k}(n) - \sum_{p=1}^{N_c} a_{(\lambda_k,p)} II_p(n)\right)^2}\right).$$

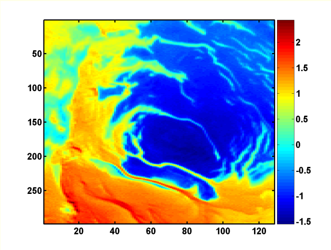


(d) Minimum spatial SNR

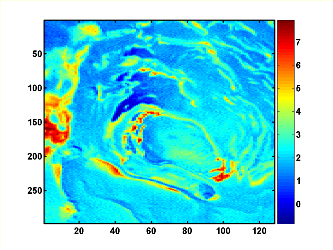
* Estimated independent components



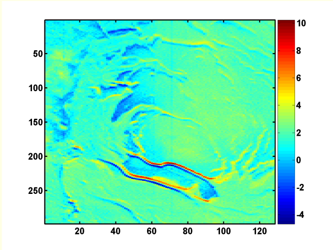
(e) Component 1



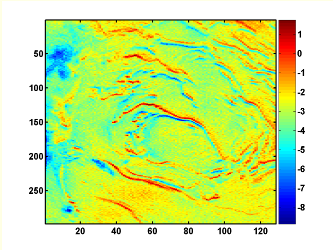
(f) Component 2



(g) Component 3

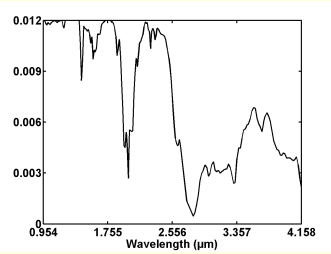


(h) Component 4

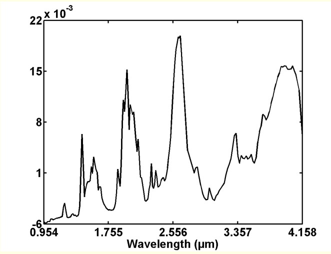


(i) Component 5

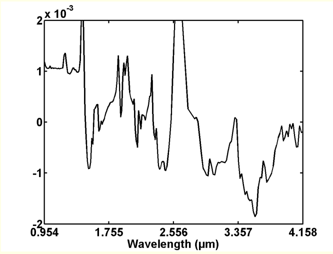
* Estimated mixing coefficient profiles



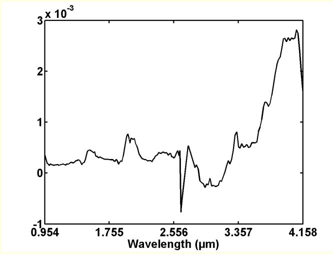
(j) Component 1



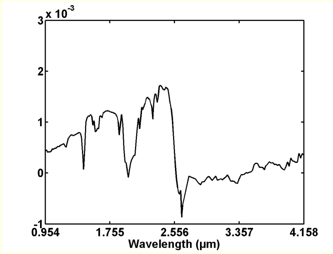
(k) Component 2



(l) Component 3



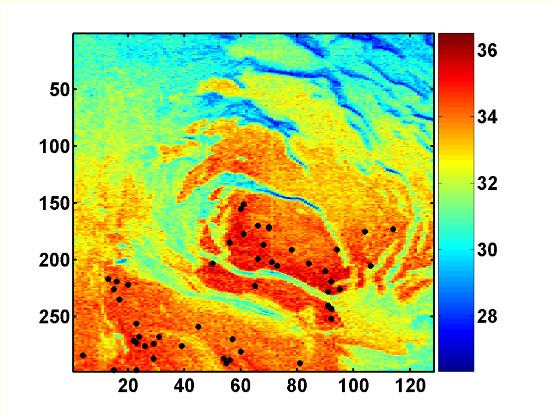
(m) Component 4



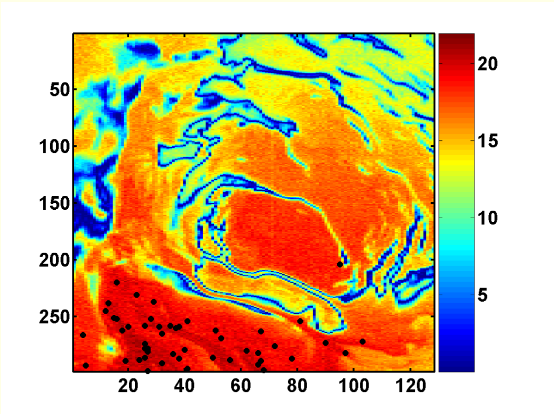
(n) Component 5

⊛ Selection of most relevant pixels

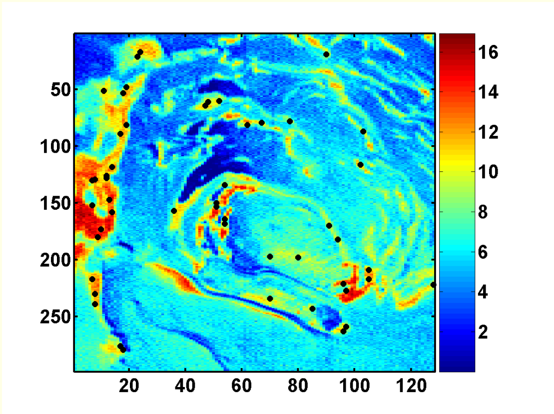
$$SNR_j(n) = SNR(n) - 10\log_{10}\left(\frac{\sum_{k=1}^{N_f} I_{\lambda_k}(n)^2}{\sum_{k=1}^{N_f}\left(I_{\lambda_k}(n) - \sum_{p=1,p\neq j}^{N_c} a_{(\lambda_k,p)} II_p(n)\right)^2}\right).$$



(o) Component 1



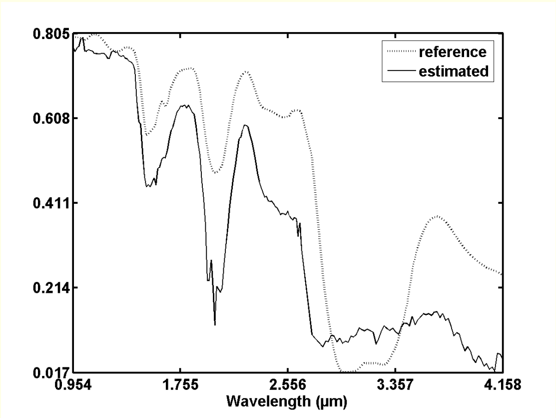
(p) Component 2



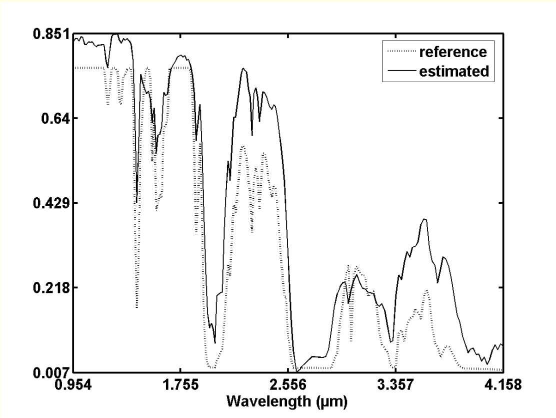
(q) Component 3

⊛ Bayesian spectral separation with positivity constraint

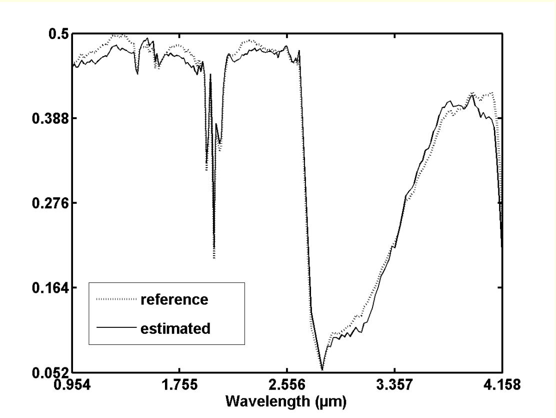
* Estimated spectral sources



(r) H_2O ice



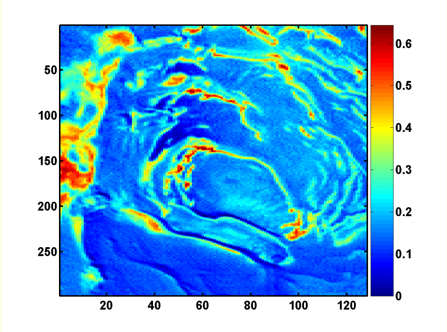
(s) CO_2 ice



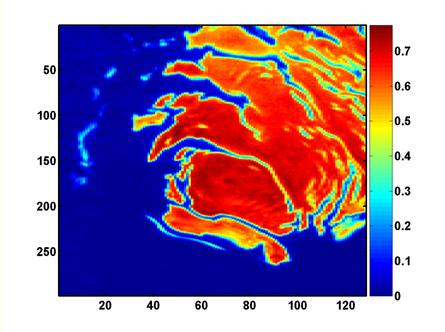
(t) dust

$$\mathbf{R} = \begin{bmatrix} 0.79 & \mathbf{0.91} & 0.87 \\ \mathbf{0.96} & 0.89 & 0.55 \\ 0.65 & 0.72 & \mathbf{0.99} \end{bmatrix}$$

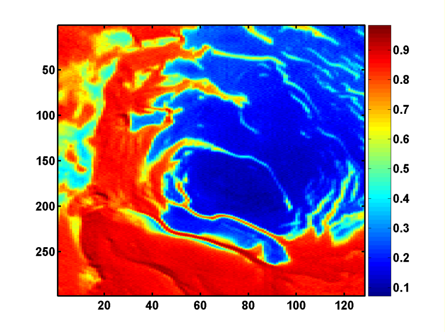
∗ Estimated abundance fractions by BPSS



(u) H_2O ice

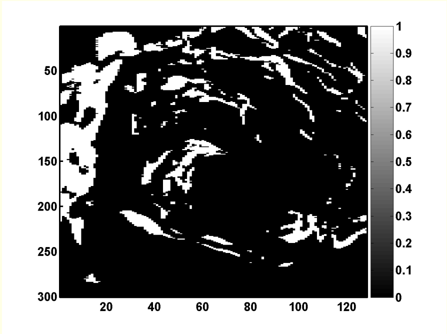


(v) CO_2 ice

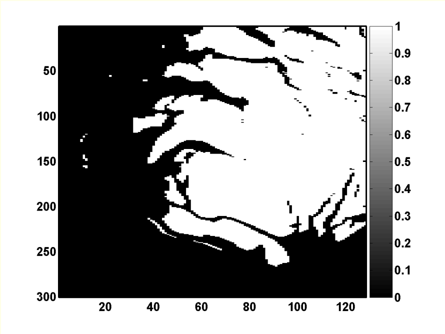


(w) dust

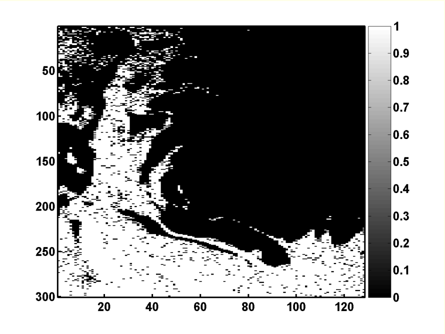
∗ Estimated abundances by Wavelet classification



(x) H_2O



(y) CO_2



(z) dust

Conclusions and future works

– application of sources separation approaches to hyperspectral data analysis in the case of geometrical mixtures,

– estimation of the number of spectral sources in the BPSS approach,

– modelling and analysis of hyperspectral data acquired from intimate mixtures (non-linear mixing models),

– how to retrieve the atmospheric attenuation ?