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ICA applied to imaging spectroscopy remote sensing

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Abstract

A comparison of Principal Components Analysis and Independent Components Analysis is made in the context of imaging spectroscopy of the Solar System bodies. Specific behaviors are outlined and explained, using examples from recent space-borne experiments and telescopic observations. ICA is in general a much more efficient tool to analyze spectral data cubes.

1. Introduction

Imaging spectroscopy has become a major tool to study both the terrestrial environment and planetary surfaces and atmospheres. The data consists in 3D spectral cubes providing a reflectance spectrum of each pixel on the target, usually a small surface area. They provide limited resolution imaging but detailed spectral, and therefore compositional, information.

Altogether, spectral data cubes are very strongly correlated datasets in which significant compositional contrasts translate as small differences in variance. The data analysis strategy often consists in identifying both the big oppositions and special but very localized signatures. The latter are usually small (~1% reflectance) and localized in a few spectral channels and few spatial pixels. Since they are superimposed on large variations of albedo affecting all channels, they represent a very small share of the total variance and are difficult to evidence. Since modern space experiments generate very large datasets (~1Gb / day for several years), efficient automated data analysis techniques are now required to process these observations.

2. Data model

The signal measured on a planetary surface can be described as a linear mixture of the spectra of the main units (end-members), combined with uncorrected instrumental effects and noise. In this model, the endmembers are assumed to be representative of large units with common spectral properties covering at least some pixels at the surface. For this reason, endmembers are assumed to represent geological terrains and associations of minerals (rocks), not the mineral themselves which do not combine linearly at small scale. In the case of Mars or Titan, atmospheric signatures are also expected to contribute to the signal. This model can be written as:

$$D = AS + B$$

where D is the data array (N pixels × P channels), S are the endmembers (M spectral sources × P), A is the mixing coefficients matrix (N × M), and B is the noise. The spectra of the N pixels can be seen either as observables (physical point of view) or variables (statistical point of view).

Some tools have been extensively used to identify such end-member components in data cubes, in particular linear mixing methods and Principal Components Analysis (PCA). In these cases, the data cubes are reduced to simple 2D data arrays — the spectra are analyzed independently, with no consideration for spatial proximity between pixels. PCA is based on variance analysis and is easily applied to spectral cubes. However, PCA has long been known to provide limited-accuracy results in this context.

Conversely, ACI is aiming at identifying a set of statistically independent components, i.e., such that their marginal probability distribution functions are separable. This is done in three steps: first, the variables are decorrelated with a PCA; second, the array of the main M components is normalized (whitening step); third, the components are rotated along the independent directions. Following the central limit theorem, this last step is performed by looking for the direction of maximum departure from Gaussianity. The remaining subspace is then analyzed similarly. A convenient algorithm for this step is JADE, which is based on joint diagonalization of the fourth order cumulant tensor. Because of the whitening step the resulting components are no longer constrained to be orthogonal in the variables space, which helps separating overlapping signatures. This is done at the expense of the knowledge of their sign and magnitude. JADE scales the components to unit variance, and order them according to the non-Gaussianity parameter, *i.e.*, to the level of heterogeneity they introduce in the dataset.

With both PCA and ICA, the spectral components allow the study of endmembers composition, while the coefficients can be mapped to estimate their spatial distribution.

4. Comparisons

Applications related to VIRTIS / Rosetta, VIRTIS / Venus-Express [1], OMEGA/Mars-Express [2,3], and adaptive optics observations of Mercury [4] and Ceres will be discussed.

Three major limitations often affect PCA results: 1) overlapping spectral features are not easily separated, because PCA looks for orthogonal components; 2) this situation is enforced when spectral parameters have similar variance, in which case they are not separated; 3) noise is never distinguished from signal, which commonly results in noisy components dominating more structured ones.

ICA does not present these limitations: separation of overlapping signatures or parameters of similar variance is more efficient because there is no orthogonality constraint; additive Gaussian noise is clearly separated from the signal, which makes ICA much more robust to random noise in this context. Altogether, the results of ICA are easier to interpret because independent components are closer to physical associations of variables than principal components, and minor signatures are more readily identified from the heterogeneity they introduce in a dataset.

References

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