COMPONENT SEPARATION OF OMEGA SPECTRA WITH ICA, O. Forni[1], F. Poulet[1], J.-P. Bibring[1], S. Erard[1], C. Gomez[1], Y. Langevin[1] ,B. Gondet[1] and the OMEGA Science Team, [1]Institut d'Astrophysique Spatiale, Université Paris-Sud, 91405 Orsay cedex, France, Olivier.Forni@ias.u-psud.fr.

Introduction: Reflectance hyperspectral observations in the visible and near-infrared domain are very powerful to infer the composition of the surface and/or atmosphere of planetary bodies. The OMEGA spectra [1] on board Mars Express consist of 352 spectral channel ranging form 0.3 to 5.1 µm with a spatial resolution ranging from 300 m to 4.8 km. One goal in the analysis of such data is to identify zones that are spectrally different from each other and to determine their composition. Statistical method like Minimum Noise Fraction (MNF [2]) combined with Pixel Purity Index (PPI [3]) have proved to be very efficient to identify mineralogical endmembers in spectra. The OMEGA dataset is very large (several tens millions of spectra acquired so far) so that the use of classical methods (spectral ratio, MNF combined with PPI) of identification is limited and not efficient in some cases. Here we will present the results obtained by another purely statistical method based on the determination of independent sources mixed linearly, namely the Independent Component Analysis (ICA) method. In this work, we have restricted our analysis to the SWIR-C detector that ranges from 0.96 to 2.55 µm.

Description of ICA: The Independent Component Analysis (ICA) derive from the Blind Source Separation (BSS) problem that consists of retrieving *n* unobservable sources from *m* linear combinations (*m* >= *n*) provided by sensors. The linear mixing problem assumes that detected signals can be written in a matrix form as

$$X = Y + N = AS + N,$$

where X represents the detected signals, Y the mixed signals, A the mixing matrix, S the unobservable source signals and N the noise introduced by the sensors. Most of the algorithms used to identify S are based on the assumption that the signals are statistically independent sources whose probability distribution function is non-Gaussian. These algorithms then tend to optimize contrast functions computed from the estimation of non-Gaussianity through neg-entropy, like in FastIca [5] or through fourth-order cumulants like JADE [4]. In the present work, we have used the JADE algorithm. The choice of the subset of components to retrieve among the *n* possible is a free parameter but the method is robust enough to be insensitive to that choice.

Results: We have applied the ICA method on some OMEGA sessions and we will present some results obtained on one orbit covering the South Pole region where H_20 and CO_2 ices were identified [] and on orbit 314_1

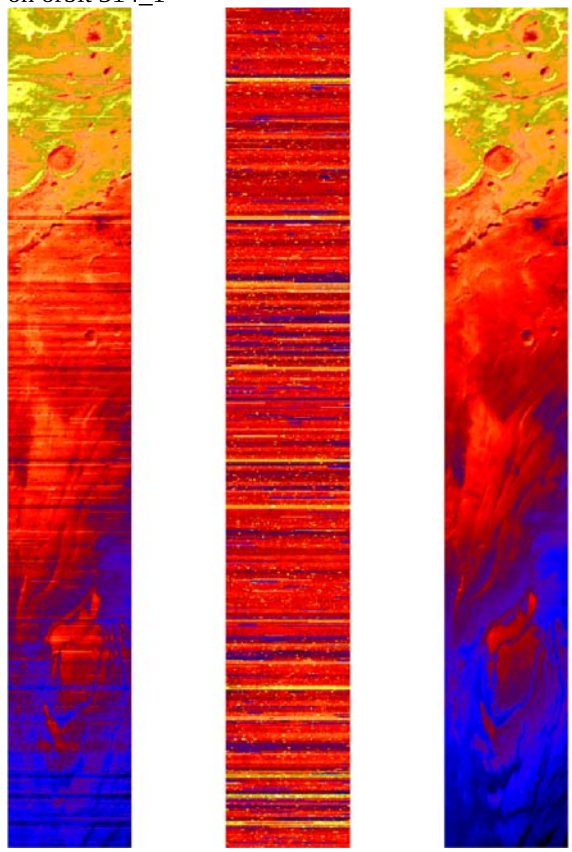

Figure 1. OMEGA track covering the South Pole during the southern summer. Left panel: original channel 88 corrupted by noise; middle panel: ICA component of the noise; right channel: denoised channel.

Denoising: We first demonstrate the ability of ICA to isolate the noise present in one specific channel. The algorithm find as one of the independent component the noise related to that specific channel, because it is non-Gaussian distributed. It is then straightforward to remove it to clean the channel (fig. 1).

Mineralogical identification: On the same observation session, the JADE algorithm finds two components that are spatially decoupled (fig. 2). The mapping of each component is straightforward since they are homothetic to the observation session.

From these components, it is possible to retrieve the spectrum of each component and we find that their spectrum correspond to those of the H_20 and CO_2 ices (fig. 3).

The same procedure detects without any a priori knowledge on the composition, a fayalite rich component (fig. 4) in the basement of two craters in orbit 314_1.

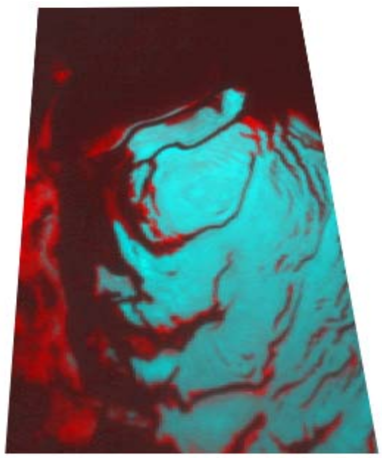

Figure 2: Colour composition of the two ices components retrieved by ICA, the red one is the H_20 component and the blue one the CO_2 ice component.

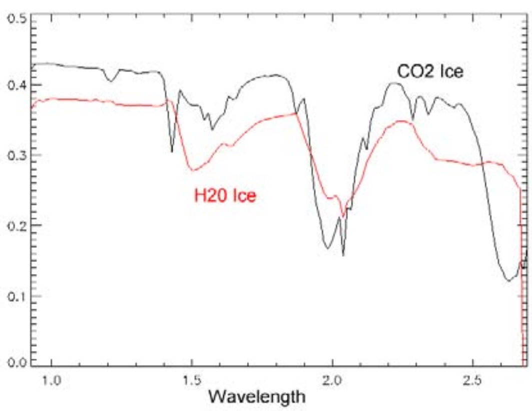

Figure 3: Spectra of the two ice components automatically retrieved by ICA.

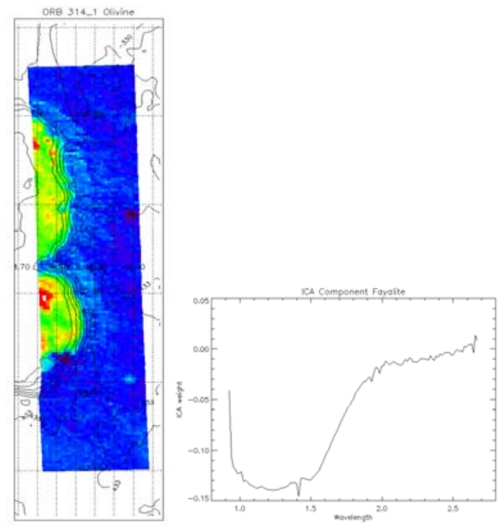

Figure 4: Detection of the fayalite rich component and associated spectrum obtained by ICA

Discussion and conclusion: The ICA component analysis is a fast and efficient tool that has proven for the first time to detect in hyperspectral data spatially independent component that can be either a non-Gaussian noise component either spectrally characteristic components whose spectra can be automatically retrieved without any a priori knowledge. ICA, as applied her, does not find spectral endmembers but rather identify zones that are spectrally very different each from another. It must be noted that ICA assumes linearly mixed components that may be a rather simple assumption and may not always be the case. The best counter example is the absorptions due to the atmosphere that are exponentially mixed. Anyway this method is very robust and will be systematically applied in the processing of the huge amount of OMEGA data.

References: [1] Bibring et al. (2004) ESA SP-1240, [2] Boardman et al., 1994, *Proc., ERIM Tenth Thematic Conference on Geologic Remote Sensing*. [3] Boardman et al., *Summaries, Fifth JPL Airborne Earth Science Workshop, JPL Publication 95-1,. 1*. [4] Cardoso & Soulomiac, (1993) IEE Proc, 140, 362, [5] Hyvärinen (1999) IEEE Trans. Neural Nettworks, 10, 626.