LEAST DEPENDENT COMPONENT ANALYSIS FOR TRACE GASES RETRIEVAL FROM SATELLITE DATA

Pia Addabbo, Maurizio di Bisceglie, Carmela Galdi
Università degli Studi del Sannio, Communications and Remote Sensing Laboratory
Piazza Roma 21, I-82100, Benevento, Italy

1. Introduction

Recent research has proved that **hyperspectral satellite observations** can be successfully used to map atmospheric trace gases throughout the planet.
Differential Optical Absorption Spectroscopy is the most widely used approach.
In this work we propose a new method to separate contributions from different atmospheric trace gases: the case of sulphur dioxide (SO_2) is considered.
The main idea is to use a portion of the absorption waveform and the **Blind Source Separation** method.

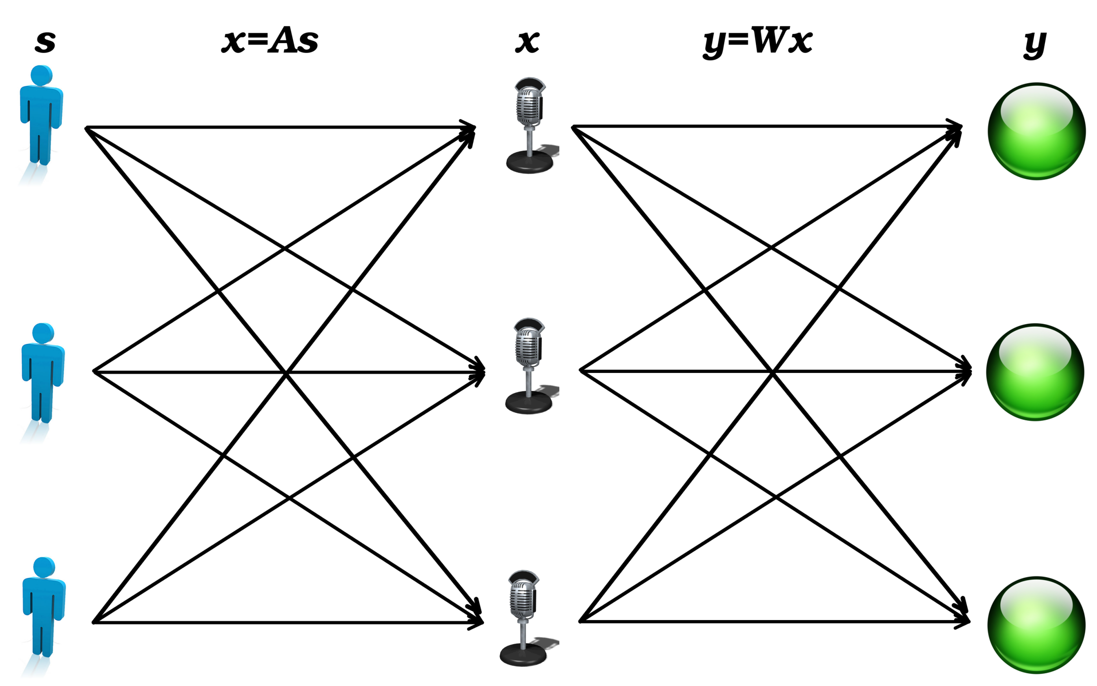

Figure: Cocktail Party illustration

The negative logarithm of the reflectance spectra can be expressed as a linear combination of absorption cross sections in their concentrations (**Beer-Lambert law**)

$$-\log(R(\lambda)) = -\log\left(\frac{\pi I(\lambda)}{\mu_0 E(\lambda)}\right) = l\sum_i n_i \sigma_i(\lambda) \quad (1)$$

where

- $R(\lambda)$ is the reflectance,
- $I(\lambda)$ is the Earth radiance,
- $E(\lambda)$ the solar irradiance,
- μ_0 the cosine of the solar zenith angle,
- l the path length [cm],
- n_i the gas concentrations along the path [mol/cm^3],
- $\sigma_i(\lambda)$ their absorption cross-sections [cm^2/mol].

Direct application of a source separation algorithm to the model (1) is not appropriate for TWO MAIN REASONS...

2. Least Dependence

Scattering from air molecules, areosols and clouds as well as absorption from the ground usually varies smoothly with wavelength and represents a source of dependence.

HIGH PASS FILTERING PRE-PROCESSING

3. Problem Formulation

The presence of all sources in any reflectance spectrum cannot be always assumed; thus we may have an **ill-posed problem**.
To overcome this difficulty, a known **contamination** is introduced in each observation.
Supposing for simplicity $m = n$

$$\begin{aligned} x_1(\lambda) &= -\log(R(\lambda)), \\ x_2(\lambda) &= -\log(R(\lambda)) + c_1\sigma_1(\lambda) \\ &\dots \\ x_n(\lambda) &= -\log(R(\lambda)) + c_{n-1}\sigma_{n-1}(\lambda) \end{aligned} \quad (2)$$

where c_i is the contamination factor.

4. Convergence

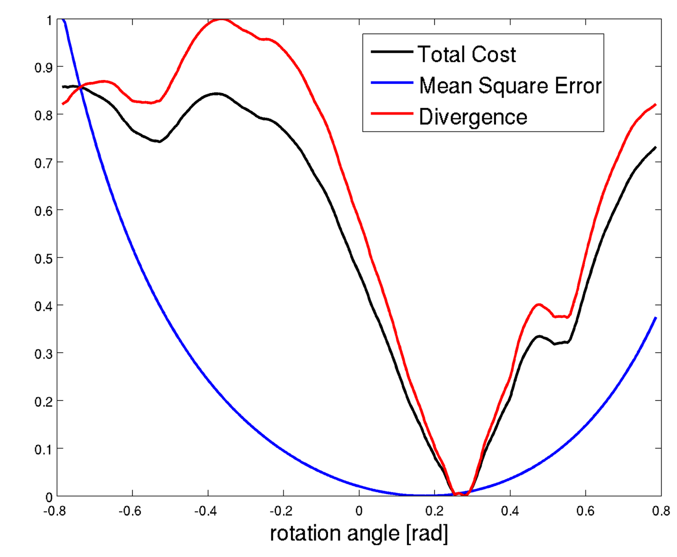

Figure: Cost functions vs rotation angle θ

5. Results and conclusions

The procedure has been applied to the retrieval of sulphur dioxide SO_2 volcano emission using data from the NASA **Ozone Monitoring Instrument** (OMI) and the SCIAMACHY preflight model SO_2 absorption cross section as reference spectrum.

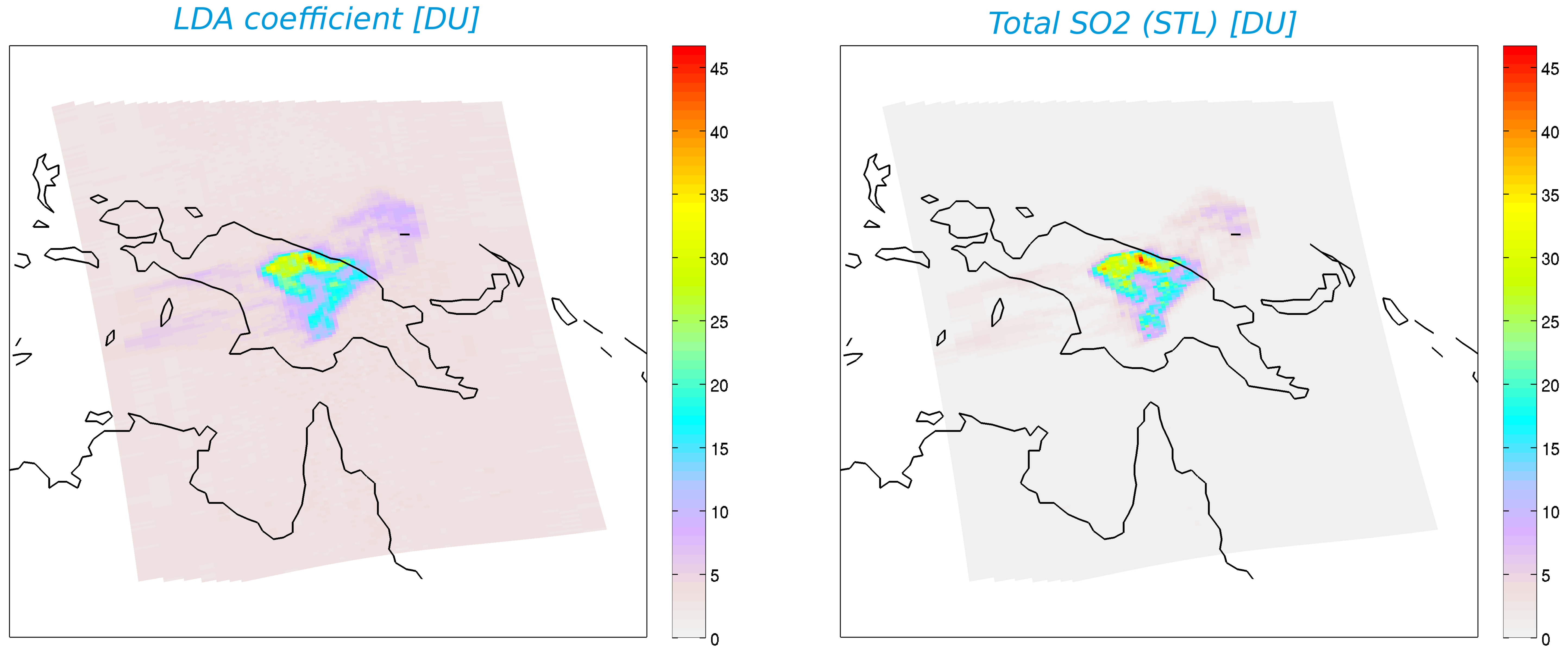

Figure: SO_2 concentration from **Manam volcano eruption (January 28, 2005)** using: Left) Least Dependent Analysis, Right) OMI team Linear Fit algorithm.

By comparing the two images, we observe that the LDA algorithm correctly detects the SO_2 plume.
The procedure can be applied to other hyperspectral sensors like the ESA SCIAMACHY.
In view of retrievals of different atmospheric components, results seem to be promising, but refinements are necessary in some contexts to get the most accurate results.

→ 5th ESA EARTH OBSERVATION SUMMER SCHOOL ON EARTH SYSTEM MONITORING & MODELLING