Fellowship ASI-CONAE (2005)

"Independent Component Analysis strategies for extracting information from remote-sensed images"

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Monthly Report. **December 2005.**
(The Final Report is included in Part IV)

Contents

Part I
Report structure

Every monthly report will be an updated version of the previous report. In this way, it will be clearly identified the developed tasks for each month and, at the same time, it will allow the reader to understand and follow all my work from the beginning of the fellowship until the present.

This document is organized as follows: In Part II, the original plan (which was agreed before the travel to Italy) is included; in Part III, a list of activities developed by me for each month of my stay is included, in Part IV, some sections to be included in the final report are presented, this last part will be updated in future reports and it will contain the structure of the final report.

Part II
Original Plan

In order to concentrate all the information about my work in only one document, the original plan, as was agreed before my travel to Italy is here reproduced. This plan was originally proposed by Mr. Emanuele Salerno in May 2005 and finally confirmed by ASI-CONAE in **August 2005**.

Title: Independent Component Analysis strategies for extracting information from remote-sensed images.

Aim: A support to the extraction of information from images coming from remote sensing platforms.

Context: The next generation of earth observation satellites will yield images with high spatial, spectral and temporal resolution. In order to separate homogeneous regions from panchromatic or narrowband images, we should rely on morphology or texture analysis. The expected availability of remote-sensed data with sufficient spatial, spectral and temporal resolution, however, allows us to devise extraction or separation techniques based on the spectral signatures of the different components. In principle, this could at least offer two advantages:

1) The homogeneous components to be extracted do not need to be spatially separated.

2) The features to be extracted do not need to be known in advance: the thematic information can be extracted on the basis of normally available additional knowledge.

The availability of high-resolution data, even though they come from different sensors or platforms, can highly favor spatial registration when needed. "Blind" analysis is independent of the features to be extracted from the data sets, and thus, depending on the kind of images that will be available, it could also be useful to assess the performance of the techniques developed in separating any kind of statistically distinct patterns.

Research program for a 4-month stay: In consideration of the past experience of the candidate, the work program does not need any preliminary study of basic material. In particular, his skills in blind source separation can be easily integrated in the activities of the research group at ISTI, and significant results can be reasonably expected in the analysis of still images, despite the short time allowed. On the other hand, if the stay of Mr. Caiafa will result in a mutually fruitful collaboration, the Laboratory will also be able to support it in the future. The experience of Mr. Caiafa in dynamic system analysis could also bring new results in the differential analysis of remote sensed images or in the extraction of kinematic parameters from temporal sequences of images. Other parts of the experience of Mr. Caiafa that are of specific interest to the research group are the development of geographic information systems, SAR signal and image processing, and satellite image registration. The task assigned to the candidate will be to try methods of blind source separation on different images coming from remote sensing platforms, in order to extract image components possibly useful for long-term or emergency risk assessment, or as a support in planning and decision making of territorial management bodies. The work can include a preliminary selection of the classes of "objects" to be extracted from the data maps, and a consequent selection of the most useful remote sensed images.

These activities will be included in the CNR subproject ICT.P03.009.006 on industrial and medical diagnosis, management of cultural heritage, and management of states of emergency (responsible Emanuele Salerno), whose activity should start later this year.

Part III
Fellow student activities

1 October 2005 activities

The following activities were done by me during October 2005 and based on the original plan of work as presented in Part I.[1]

- **Bibliography survey:** An extensive survey of bibliography was performed. The idea was to search for previous published papers where techniques like Independent Component Analysis (ICA) were used in the context of remote sensed imaging applications. The following specialized Journals and resources were consulted:

- IEEE Transactions on Geoscience and Remote Sensing.
- IEEE Geoscience and Remote Sensing Letters
- IEEE Signal Processing
- International Journal of Remote Sensing.
- Proceedings of several Conferences on Remote sensing applications
- Documentation at Purdue University site regarding Multispectral data model and analysis (http://dynamo.ecn.purdue.edu/)

Most representative papers are included in the reference list of Part IV.

- **Bibliography reading:** Papers and documentation were deeply read and studied. As a result of this reading, it was identified the Spectral Unmixing task as the most interesting one to be developed during the fellowship. The following paper was selected as a base for the experiments to be carried out at ISTI.

[23]: J. M. P. Nascimento, and J. M. Bioucas Dias, "Does Independent Component Analysis Play a Role in Unmixing Hyperspectral Data?", IEEE Transactions on Geoscience and Remote Sensing, Vol 43, No 1, January 2005.

In the corresponding sections on Part IV an explanation about the spectral unmixing task, the model presentation and the techniques currently used will be included.

- **Algorithms selection:** As is indicated in [23], one of the main problems for ICA algorithms to be useful for Unmixing Hyperspectral Data, is that in reality, the components to be extracted (material abundances) are not independent. In fact, the summation over all the abundances is constrained to be 100% imposing a strong dependence on sources. For that reason, it is interesting to use new algorithms specially designed to

[1] Some activities were also done during September 2005 while I was waiting for the final arrangement of my travel to Italy.

work in the dependent sources context. For my fellowship, it was decided to work with the algorithm presented in [4] and to compare the results with the ones obtained by FastIca algorithm which was used in [23].

- **MaxNG algorithm arrangements:** The MaxNG algorithm was set up, some parts were optimized, for example, a deflation step were introduced after each local maximum search iteration.
- **Experiments proposal:** In order to test if MaxNG works OK or not for this kind of dependent sources (abundances) and to compare with FastICA algorithm, a set of experiments were proposed:

A) **Synthetic data:** To generate abundances according to a given probability density function, generate mixtures using spectral signatures and try to separate sources for the following cases:

A1- Independent sources

A2- Dependent sources, where the constraint on the abundances summation is imposed.

A3- Adding noise

etc.

Note: some experiments for cases A1 and A2 were performed during October. The results will be reflected in the corresponding sections of Part IV.

B) **Real data:** To apply algorithms to the same data analyzed in [23] and to compare results.

Note: This kind of tests will be included in future reports.

2 November 2005 activities

- **Experiments were documented:** Many experiments were repeated and completed for documenting purposes. Separation of synthetically mixed signals were made using two standard ICA algorithms: FastICA and JADE and the results were compared with the MaxNG algorithm. Sources were randomly generated using uniform pdfs for independent and dependent cases (see below). Random and real world spectra were used for the simulations (see below). Also preliminary results on a real image (AVIRIS) were obtained. The following tests were performed and documented:

A1- Independent sources (see section 7.1.1 for the result details): in this case, uniform independent sources were used. Mixing matrix was randomly selected.

A2- Dependent sources (see section 7.1.2): in this case, sources were constrained to the dependent case and two cases for the mixing matrix were considered (see below).

I- Random Mixing Matrix

II- Mixing Matrix with real world spectra: (real spectra from an Aviris Image were obtained using a ground truth as provided by [23])

A3- Adding noise to the model: (to be including in forthcoming reports)

A4- Hyperspectral data (see section 7.2): A real AVIRIS image were used to test the results of applying the algorithms and compare the results with those presented in [23]. Used data is shown in section 7.2, Figure 3 and results will be included in forthcoming reports.

- Sections of final report were filled (see sections 5 and 7.1)
- A Seminar was given to the ISTI: "Separation of statistical dependent sources using a measure of non-Gaussianity", C. F. Caiafa. Seminar at the "Signal & Images Laboratory of ISTI"- CNR, 9^{th} Nov. 2005, Pisa, Italy. ([3])

3 December 2005 activities

- **Experiments were continued and documented:** Following with the experiments, the noisy model case was analyzed comparing ICA algorithm with MaxNG. Also Hyperspectral data was used (see sections 7.3, 7.2.1 and 7.2.2)

A3- Adding noise to the model: Comparisons between JADE and MaxNG were performed for different levels of noise. Mean SIR (Signal to Interference Ratio) versus SNR (Signal to Noise Ratio) were calculated for both cases (see Figure 2)

A4- Hyperspectral data (see section 7.2): Two sets of real images were used to test the results of applying the algorithms MaxNG, FastICA and JADE and to compare the results with those presented in [23]. The data used were:

- One AVIRIS image (see same used in [23]) which is shown in section 7.2.1, Figure 3.

- One MIVIS image provided by a CNR Institute at Rome (Istituto sull'Inquinamento atmosferico) which is presented in section 7.2.2

- **The final report was produced (see Part IV of this report)**

Part IV

Final Report

Title: "Independent Component Analysis strategies for extracting information from remote-sensed images"

4 Introduction

Independent Component Analysis (ICA) algorithms have been deeply studied during the last 10 years and its potentials have been highlighted in the bibliography for a broad class of engineering applications (see for example the books [5] and [24]).

ICA can be considered as a particular case of a more general problem called Blind Source Separation (BSS). In general, a BSS algorithm intends to provide an good estimation of the input signals of a linear system when the only available information are the outputs of the system. A very known fact is that, in order to have a well posed problem, input distributions are not allowed to be Gaussian ([24]). These methods are called "blind" since no information is available about the input signals neither on the linear mixing process.

The most popular way to approach the BSS problem is to assume independence of sources, which is the most deeply studied case and it is known as simply ICA. Using the fact that sources are independent, they can be estimated from the mixtures minimizing the "mutual information" of estimates and using mathematical tools of the Information Theory created by C. Shannon in 1948 ([27]). It is interesting to note that, in case of imposing independence of sources estimates, minimizing mutual information is exactly the same as maximizing a non-Gaussianity measure of estimates ([7], [24]).

The separation of dependent sources were not approached by many researchers during the past. In [4], it was shown that some dependent sources can be successfully separated using a non-Gaussianity measure based on the euclidean distance of probability distributions and calculated using Parzen windows technique.

A direct application of BSS algorithms is the spectral unmixing problem in remote sensing images, where it is assumed that each pixel, in a specific spectral band, is composed by the contributions (abundances) of different material (end member) spectra ([13]). Some papers have been recently published with applications of ICA algorithms for pixel unmixing and some promising results were presented although many issues are still open to solve ([1], [10],[11], [14], [18], [21], [22], [23], [25], [29], [30], [31]).

One of the known problems of ICA algorithms to perform spectral unmixing is that sources are not really independent ([23]) and new techniques should be developed. Additionally, noise is always present in real images and most of ICA algorithms have some problems to deal with it.

This final report is organized as follows: in section 5, the mathematical formulation of the spectral unmixing problem is stated and linked with the BSS framework, also FastICA, JADE and MaxNG are briefly discussed; in section 6, the objectives of the present work are presented; in section 7, all the obtained experimental results are presented for different types of synthetically generated data as well for some real images datasets; finally in section 8, the main conclusions and issues to be included in a future program are outlined.

5 Hyperspectral Data Unmixing

Under certain conditions (see [23], [13] and all the references therein for the details), it can be considered that the spectral radiance upon the sensor location is well approximated by a linear mixture of end member radiances weighted by the correspondent fractional abundances and an additive noise. This is called the linear mixing model and basically, it is valid when multiple scattering among distinct end members is negligible and the surface is partitioned according to the fractional abundances ([13]).

A very simplified linear mixing model, for M sensors (bands) and P end members (materials) can be written in the following way:

$$\mathbf{x} = A\mathbf{s} + \mathbf{n} \tag{1}$$

where $\mathbf{x}$ is a $M \times 1$ vector which contains the measures for each band, A is the mixing matrix ($M \times P$) which contains the signatures of the end members present in the coverered area and $\mathbf{n}$ is a $M \times 1$ vector containing the electronic system noise and other introduced errors like signature variability ([23]).

5.1 Mathematical formulation.

In this subsection we restrict the analysis of the linear mixing model (equation (1)) to the noiseless case for simplicity purposes, i.e., we consider the following model:

$$\mathbf{x} = A\mathbf{s} \tag{2}$$

In this simple model, the estimation of sources is linear on the mixtures, it means that sources can be estimated finding the separation matrix D that verify the following relation:

$$\widehat{\mathbf{s}} = D\mathbf{x} = DA\mathbf{s} = W\mathbf{s} \tag{3}$$

where the matrix W is a permutation and/or scale matrix ([7], [24]).

Any BSS algorithm consists in a method of finding the separating matrix D. In the case of absence of noise, sources are directly calculated using equation (3).

When the sources are known to be independent, we are in the framework of ICA and the most popular way of obtaining the separating matrix is to look at the Mutual Information of sources estimates and select the separating matrix that minimize it. But, when sources are not independent, other criteria must be taken into account.

5.2 BSS - ICA algorithms

In general, there are more mixtures than sources, for example for hyperspectral images like Aviris, the number of sensors (mixtures) is $M = 220$ and the expected number of classes (sources) can be, for example, $P = 10$. For this reason, the available data (mixtures) are redundant and the real dimension of data is significantly lower than the number of mixtures. To reduce the dimension of data the classical Principal Component Analysis (PCA) is usually performed. This step is commonly referred to in the literature as an sphering or spatial whitening. The spatial whitening step comprises the following linear transformation:

$$\widetilde{\mathbf{x}} = \Lambda^{-1/2} V^T \mathbf{x} \tag{4}$$

where V is a $Q \times Q$ ($Q \leq P$) matrix of eigenvectors of the covariance matrix $R_{\mathbf{xx}} = E[\mathbf{x}\mathbf{x}^T]$ and Λ is a diagonal matrix containing the Q non-zero eigenvalues of $R_{\mathbf{xx}}$([2]).

Note that the purpose of the of equation (4) is twofold: first, it allows us to work with a dataset $\widetilde{\mathbf{x}}$ which has lower dimension (Q) than the original dataset $\mathbf{x}$ (M); and second, it provides a new dataset which is composed by uncorrelated variables ($R_{\widetilde{\mathbf{x}}\widetilde{\mathbf{x}}} = E[\widetilde{\mathbf{x}}\widetilde{\mathbf{x}}^T] = I$) (see [4] or [24] for details).

To obtain the separation matrix, it is needed to search the separating matrix that maximize or minimize any particular criteria. For the case of ICA algorithms, one of the most preferable cost functions is the Mutual Information ([24]), instead, when sources are dependent it is better to maximize the non-Gaussianity of estimates ([4]). Some of the most representatives algorithms for ICA are FastICA ([12], [5]) and JADE ([5]) which are briefly discussed in following sections. Also a new algorithm (MaxNG ([4])) specially designed for the separation of dependent sources is described below.

5.2.1 FastICA

Hyvarinen and Oja proposed a family of batch learning rules, called fixed-point or FastICA algorithms for a hierarchical neural network that extracts the source signals from their mixtures in a sequential fashion. Sources are linear in the whitened mixtures $\widetilde{\mathbf{x}}$, therefore a parameterization of sources estimates is $y = \mathbf{w}^T \widetilde{\mathbf{x}}$, where vector $\mathbf{w}$ is constrained to be unit-norm ($\|\mathbf{w}\| = 1$) since y

[2]Note that, if no noise is considered in the model, and if P sources are linearly independent, then the number of non-zero eigenvalues is P. With real data, noise presence makes all eigenvalues to be non-zero but many are very close to zero and can be discarded.

must have unit variance. (see [5] for details). Then, in FastICA, sources are obtained one by one maximizing the following cost function:

$$\Gamma_{FastICA} = E\left[G(\mathbf{y})\right]$$

with $E[.]$ being the expectation operator, and $G(y)$ is a non-linear convex function. It is interesting to note that, if $G(y) = y^4$ then FastICA maximizes the kurtosis of the sources estimates, which is a way of maximize their non-Gaussianity ([24]).

5.2.2 JADE

In the JADE (Joint Approximate Diagonalization of Eigenmatrices) algorithm, in contrast to FastICA, the estimation is not sequential and all the sources are obtained at the same time. Source estimates are chosen in a way that they jointly diagonalize a set of contracted quadricovariance matrices ([5]). This method can be seen as a direct generalization of PCA for higher order statistics (see [5] for all the details of the algorithm).

5.2.3 MaxNG

MaxNG, introduced in [4], is similar to FastICA in the sense that it also obtains sources estimates in a sequential way but, not independencies between sources is imposed, and the non-Gaussianity measure $\Gamma(p_y)$ of a probability density function (pdf) p_y is based on the euclidean distance between p_y and the Gaussian pdf, i.e. $\Gamma_{MaxNG}(p_y) = \int \left[\Phi\left(y\right) - p_y(y)\right]^2 dy$ (see [4] for all the details of the algorithm).

6 Objectives of the present work

The application of blind techniques to remote sensing images would give a valuable tool for classification tasks and may be used in addition to traditional techniques.

But it is important to highlight that BSS algorithms applied to remote sensed images go beyond simple classification. In theory, they would be able to determine each material percentage per pixel. In other words, BSS techniques may allow the user to see inside pixels and characterize the covered area in a more detailed way.

The main objective of this work is to analyze how different BSS algorithms perform for the spectral unmixing task. As it is well known, material abundances are not independent in real images and, while ICA algorithms were already used in the literature with some promising results, it is expected that MaxNG, which is designed for dependent sources can provide better results.

Another interesting issue to be investigated is how noise may affect the results. Many experiments are proposed using datasets synthetically generated in order control the level of noise, which in real images is very difficult to measure.

7 Production of experimental results

In this section all the obtained results are presented and are divided in two main groups depending on the type of the used data: synthetic data (section 7.1) and real world data (section 7.2). In the first group of tests (synthetic data) we were interested in analyzing and comparing how FastICA, JADE and MaxNG perform for independent and dependent sources, and different types of mixing matrices are proposed (see next sections). In the second group of tests (real world data) we apply the algorithms to real images and evaluate the performance of the algorithms.

7.1 Synthetic data

In this subsection, MaxNG is compared with two classical ICA algorithms: FastICA ([12]) and JADE ([8]). Sources are randomly generated and mixtures are produced using a known mixing matrix, then sources are estimated using the three algorithms and performance is evaluated for each one. In order to quantify the level of accuracy in the estimation process, a measure of closeness of source estimates $\widehat{s}_i$ to original sources s_i is used. Defining the error vector as the difference between unit-variance original source vector and its unit-variance estimate $\mathbf{e} = \widehat{\mathbf{s}} - \mathbf{s}$, we use the Signal to Interference Ratio (SIR) as it is usually used in the literature, defined, for source i as

$$SIR_i = -10 \log_{10}(var(e_i))$$

In general, SIR levels below 10-12 dB threshold are indicative of a failure in obtaining the desired source separation ([2]).

7.1.1 Independent sources

In this experiment, data was generated using uniform pdfs. A total of $P = 6$ Independent sources (abundances) were generated and synthetically mixed by equation (1) using a known (randomly selected) mixing matrix A, with $P = 6$ (number of sources) and $M = 6$ (number of mixtures). Ideal mixing conditions were assumed considering no noise ($\mathbf{n} = 0$). A data length of $N = 2048$ was selected which correspond, for example, to images of 32×64 pixels. Many simulations were performed and results of using MaxNG versus FastICA and JADE were compared. In Table 1, an example is shown. Note that, in this independent source case, the three algorithms were able to recover original sources and the best performance was obtained by MaxNG algorithm.

Source	MaxNG SIR	FastICA SIR	JADE SIR
0	25.41	23.97	21.53
1	25.24	27.94	15.88
2	24.69	25.28	17.78
3	27.85	20.64	14.18
4	27.66	23.52	22.80
5	27.73	27.68	18.86
	26.43	24.84	18.51

Table 1: Independent Sources Case. SIR values in dB obtained for MaxNG, FastICA and JADE algorithms.

7.1.2 Dependent sources

Random Mixing Matrix. As explained before, in real remote sensed images, sources are not independent components. Each source corresponds to one material abundance and therefore, they are constrained to add up to 100%. This constraint produces dependent sources and makes ICA algorithms to fail or to be not very precise in recovering sources. In this subsection we compare the MaxNG algorithm with FastICA and JADE for dependent sources. We have used the same parameters as before: $P = 6$ (number of sources), $M = 6$ (number of mixtures) and data length of $N = 2048$. For the generation of sources, first a set of independent signals ($\{\widetilde{s}_j\}$) is generated and after we enforce the constraint dividing each source by the total summation, i.e. $s_i = \frac{\widetilde{s}_i}{\sum_{j=0}^{P} \widetilde{s}_i}$. It is important to note that the constraint on the abundances reduces the dimensionality of the data by one, it means that, when applying the PCA transformation to the data, one zero eigenvalue is obtained. An example of the SIR values obtained on this data is shown in Table 2. Note that, using ICA algorithms FastICA and JADE, is not possible to recover all the sources. Two sources were recovered with FastICA (SIR greater than12dB) and only one with JADE. On the other hand, using MaxNG, all the sources were well recovered reaching to high SIR values. This result confirms us that ICA algorithms like FastICA and JADE are not the best options for Hyperspectral images since sources are dependent.

Source	MaxNG SIR	FastICA SIR	JADE SIR
0	23.16	2.86	4.15
1	25.27	9.70	2.84
2	20.30	7.67	8.23
3	28.82	13.07	14.89
4	31.44	28.66	3.53
5	26.53	3.95	8.91
	25.92	10.98	7.09

Table 2: Dependent Sources Case. SIR values in dB obtained for MaxNG, FastICA and JADE algorithms.

Using real world end member spectra. In this subsection, instead of using a randomly selected mixing matrix, we will choose a more real situation using a non-square matrix where each row correspond to an end member spectrum. Real world end member spectra were obtained from an Aviris image for which a ground truth is available ([23]). In this case we consider $P = 9$ sources (materials) and a total of $M = 192$ mixtures were generated. A data length of $N = 21025$ was selected, which corresponds, for example, to images of 145×145 pixels. We also use synthetic dependent sources generated as before (uniform pdfs).

As usual, when more mixtures than sources are available, data is redundant and the dimensionality can be reduced by the PCA representation considering only the non-zero eigenvalues of the covariance matrix and their corresponding eigenvectors.

In Fig 1, end member spectra for nine classes are shown.

The results of the simulations are presented in Table 3. Note that, again, MaxNG algorithm performed better than ICA algorithms (FastICA and JADE). If we consider a SIR threshold of 12dB, for example, then FastICA and JADE algorithms produce four good estimates over the total of nine (44,44%), on the other side, MaxNG produces nine good estimates which represents the 100% of signals.

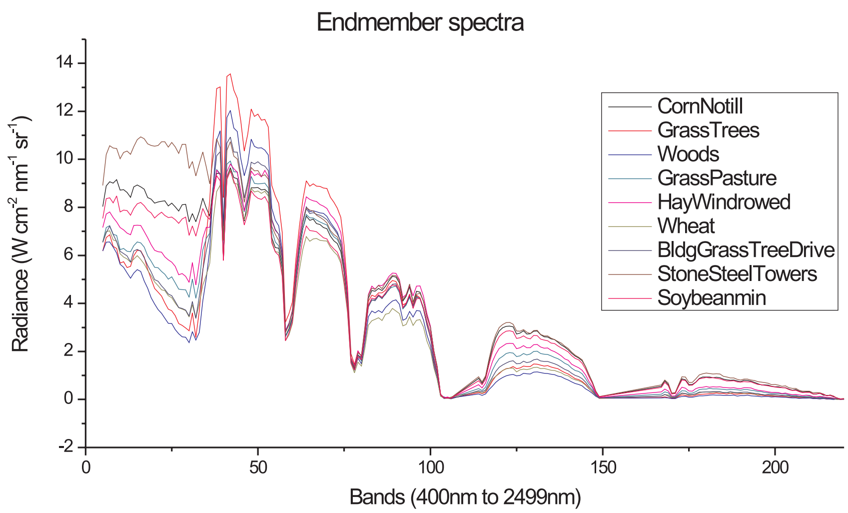

Figure 1: Endmember spectra for 9 materials present in an AVIRIS image. Measures are given in radiance units.

Source	MaxNG SIR	FastICA SIR	JADE SIR
0	36.16	12.28	10.22
1	35.92	2.10	3.86
2	33.42	14.32	1.77
3	34.68	18.11	15.65
4	32.83	8.16	12.09
5	35.63	5.33	11.44
6	41.98	10.60	16.11
7	37.17	28.69	10.73
8	34.54	3.89	14.60
	35.81	11.50	10.72

Table 3: Real Spectra Case Case. SIR values in dB obtained for MaxNG, FastICA and JADE algorithms.

7.1.3 Adding noise to the model

The idea of this section is to test how the algorithms perform in the presence of noise. Using real world end member spectra as before, mixtures were generated using equation (1). The used parameters were also as before ($P = 9$ sources (materials), $M = 192$ mixtures and a data length of $N = 21025$ (145×145 pixels image)). JADE and MaxNG algorithm were used, FastICA was avoided because it showed problems on convergence and it may take a long time to obtain many result for different SNR values.

The SNR was controlled through the variance of the noise, it means, the SNR is defined as usual by

$$SNR(dB) = 20 \log \left(\frac{\sigma_s}{\sigma_n} \right)$$

where σ_s is the standard deviation of sources (here fixed at one-value) and σ_n is the standard deviation of noise which was set in the range of 0.01 to 0.7 ($40dB$ - $3.1dB$). Gaussian and spatially uncorrelated noise was used ($E\left[n_i n_j\right] = 0$ for $i \neq j$).

To evaluate the performance of separation algorithms, the corresponding SIR_i (dB) for each source was computed for $i = 0,\ 1, .., \ P-1$ and then the Mean SIR was calculated:

$$\text{Mean } SIR \text{ (dB)} = \frac{1}{P} \sum_{i=0}^{P-1} SIR_i$$

The results are shown in Figure 2. Note that, as expected, Mean SIR increase with SNR. What is important to note is that MaxNG proved to be more efficient than JADE for all SNR values considered. If we considered 12dB as

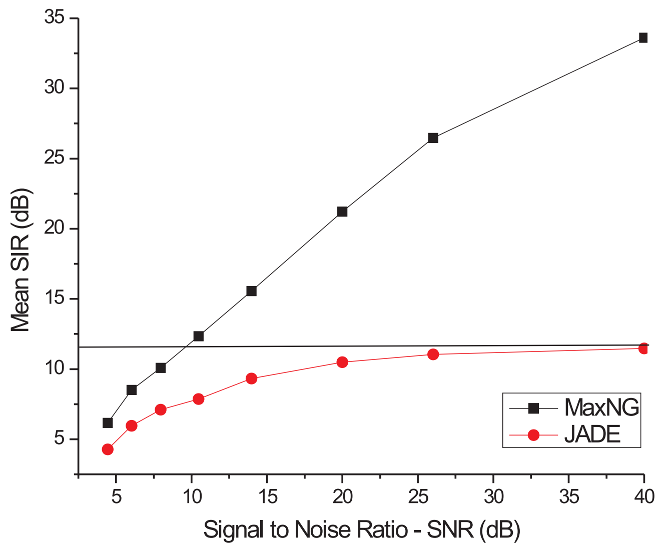

Figure 2: Mean SIR values versus SNR for MaxNG and JADE algorithms.

an acceptable threshold value for Mean SIR, then JADE was always under the threshold and MaxNG succeed for SNR in the range $10dB$ - ∞.

It is reasonable that not good results were obtained for low SNR values because ICA and MaxNG algorithms were designed for the special noiseless case.

7.2 Real world data

7.2.1 AVIRIS (Airborne Visible/Infrared Imaging Spectrometer) dataset

In this subsection we applied ICA algorithms (FastICA and JADE) and the MaxNG algorithm to a real world data set. This data set is the same used in [23] which is an hyperspectral subimage of Indian Pine Test Site in northwestern Indiana acquired by an AVIRIS instrument in June 1992. Noisy channels and water absorption channels were removed (channels 1-4, 107-113, 150-166 and 221-224). This image was provided in a processed form in which the path radiance and the light scattered by the interaction between surface and the atmosphere were removed ([23]).

In Figure 3. a), a RGB (real colors) version of the data set is shown. The dataset is composed of 220 spectral channels with 10nm bandwidth acquired in the $0.4 - 2.5\mu m$ region. It contains 145×145 pixels $(21,025)$ with a ground resolution of $17m$ ([23]).

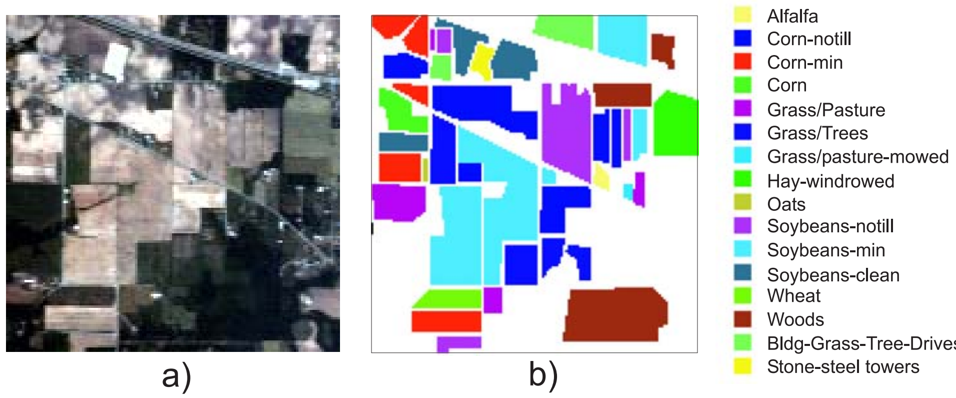

Figure 3: a) Aviris hyperspectral dataset, RGB image (channels 26(R)-13(G)-6(B)); b) ground truth provided by on site inspection (source: http://dynamo.ecn.purdue.edu/)

A ground truth for this area is available at http://dynamo.ecn.purdue.edu/ and it is shown in 3. b).

Dimension reduction The first step is to determine which is the dimension of the hidden sources, i.e., how many distinct materials are present in the mixtures. As we proceed in a totally blind approach, we don't know nothing about this number, but it can be estimated using PCA (Principal Component Analysis). As was explained before, if no noise is present in the mixtures, since we have more mixtures M than sources P, the representation of data is redundant and only P eigenvalues are non-zero. Actually, we have noise and no zero-eigenvalues are usually observed but we can see how is the curve of eigenvalues and it gives us an approximation of the dimension of the problem. In Table 4, a list of most significant eigenvalues is showed and they are ordered from the highest (top) to the lowest (bottom). As usual, each eigenvalue represent the amount of "energy" assigned to its corresponding eigenvector. It means, if we take only the first eigenvector to reconstruct the data we will reach the 72.6% of the total energy, if we take the first two eigenvectors a total of 97.3% of the energy will be reconstructed, and so on.

Eigenvalue	Percentage (%)	Total (%)
0	72.569	72.569
1	24.766	97.334
2	1.716	99.051
3	0.359	99.410
4	0.191	99.600
5	0.128	99.728
6	0.037	99.765
7	0.022	99.787
8	0.017	99.804
9	0.009	99.813
10	0.009	99.822
11	0.008	99.829
12	0.007	99.837
13	0.007	99.843
14	0.006	99.849
15	0.005	99.855
16	0.005	99.860
17	0.005	99.865
18	0.005	99.870
19	0.004	99.874

Table 4: Eigenvalues Energy

After applying the PCA dimensionality reduction, MaxNG and ICA algorithms were applied to the hyperspectral data.

Results using $Q = 5$ principal components (99.6% of Total energy) Several numbers of principal components were applied before running ICA and MaxNG algorithms. In general, after comparing the results with the ground truth provided by Figure 3, it was found that five classes were identified. In Figure 4, a comparison of classes detected by MaxNG, FastICA and JADE algorithms is shown for the case of 5 principal components. The classes detected are as follows:

Number	Description
Class 1	Woods and Grass/Pasture
Class 2	Corn and Soybean
Class 3	Routes and buildings
Class 4	Hay-windrowed
Class 5	non-classified

It is interesting to note that some classes included in the ground truth are obtained together with these algorithms, for example, in Class 1(Woods and Grass/Pasture) and in Class 2 (corn and soybean).

FastICA and JADE have produced the same outputs (see columns 2 and 3 in Figure 4) as was expected because both are ICA algorithms. On the other side, with MaxNG, similar bur not the same results were obtained. It seems that MaxNG had a little bit better performance since, for example, for Class 1, the image is more segmented than the ICA results case, showing a better separation and a lower level of noise in the estimation.

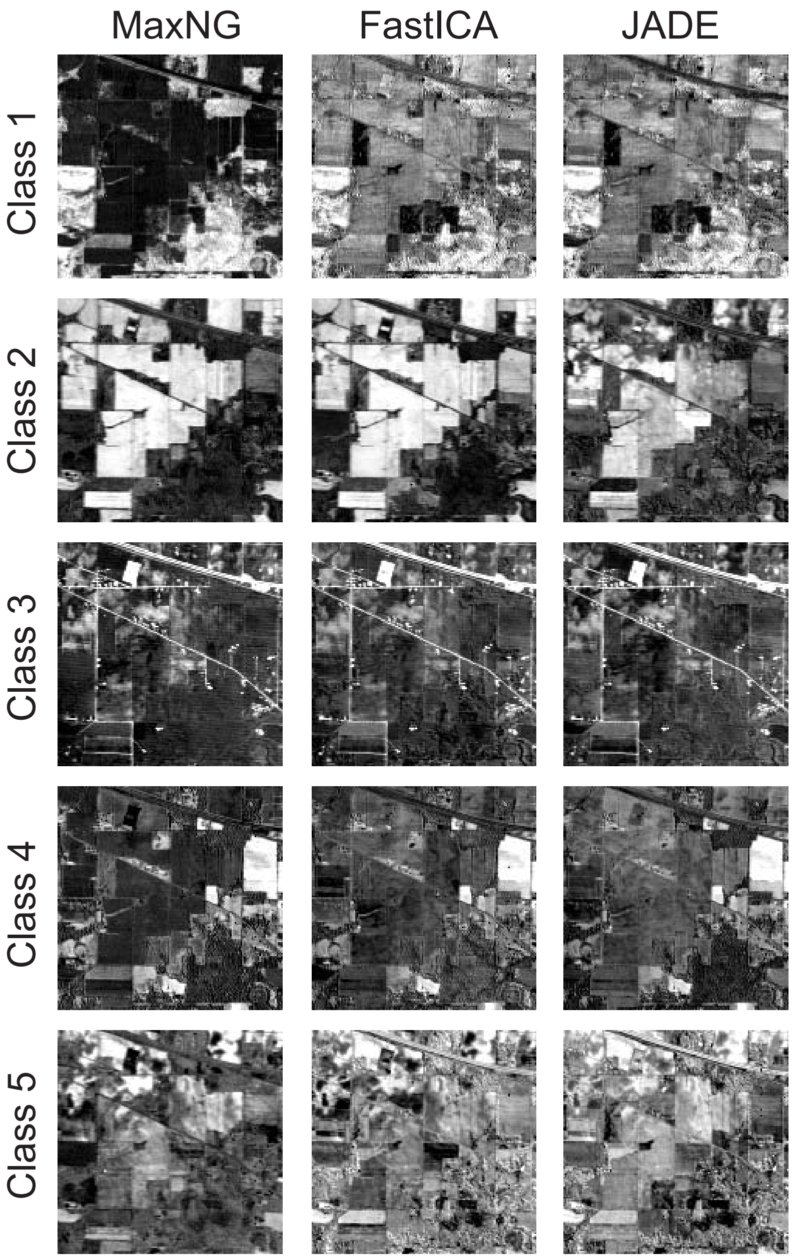

Figure 4: Obtained classes (sources) using MaxNG (left), FastICA (center) and JADE (right) algorithms.

Figure 5: Image of Roma captured with the MIVIS sensor (LARA / Istituto sull'Inquinamento atmosferico, CNR, Roma, Italy)

7.2.2 MIVIS (Multispectral Infrared and Visible Imaging Spectrometer) dataset

In this subsection we present the results of applying MaxNG algorithm to a different real dataset obtained with the MIVIS (Multispectral Infrared and Visible Imaging Spectrometer) which is a sensor property of LARA (Laboratorio Aereo Ricerche Ambientali, CNR) and the image was provided by the Istituto sull'Inquinamento atmosferico, CNR. In Figure 5 the complete image is shown in real color. The dataset is composed of 755×351 pixels and 102 spectral channels corresponding to four independent spectrometers in different bands: channels $1 - 20$ $(0.43 - 0.83\mu m)$; channels $21 - 28$ $(1.15 - 1.55\mu m)$; channels $29 - 92$ $(2.00 - 2.50\mu m)$ and $93 - 102$ $(8.20 - 12.70\mu m)$.

Also a ground truth for a specific area included in this image was provided by the Istituto sull'Inquinamento atmosferico. In Figure 6 the ground truth and the classes obtained using MaxNG for a sub image of 145×145 pixels are shown. In this example a total of 12 principal component were used. From Figure 6 a direct correspondence of classes in ground truth and our estimates can be visually stated as follows:

Ground Truth Class	**MaxNG Class**
Yellow	1
Red	2
Green	3
White	4
Brown	5

8 Conclusions and future work

The main conclusions of this work can be summarized as follows:

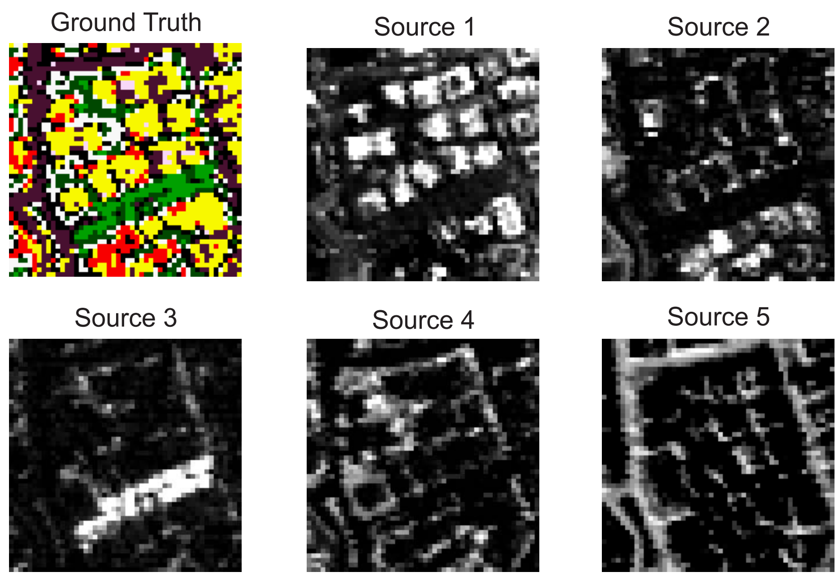

Figure 6: Ground truth (upper left) and sources (classes) estimated using MaxNG algorithm.

- Results of sections 7.1.1 and 7.1.2 have confirmed, FastICA, JADE and MaxNG produce similar results when sources and independent (Table 1) but, when signals are constrained to add up to one, they become dependent and much better results are obtained with MaxNG algorithm (Table 2 and 3)
- Results of section 7.1.3 showed that the effect of adding noise to the model is to decrease the performance of separation for JADE algorithm as well as for MaxNG as was expected. Anyway it is interesting to note that the performance of MaxNG is always much better than JADE (see Figure 2).
- Results of section 7.2 showed that FastICA, JADE and MaxNG can provide good classification on hyperspectral images. It was also verified that MaxNG provides class images with more contrast which may be is a sign of a better classification (see Figure 4).
- While MaxNG algorithm seems to perform OK for unsupervised classification, we think that maybe it is not much interesting to use it for this purpose, because it demands a lot of time (for example for an image of 145x145 it took more than 1 hour). And, there are other classical methods like Isodata or K-means that are faster. Anyway, what we think is interesting in BSS methods is that we are able to see the percentages of each material for each pixel (pixel unmixing).

In light of the present results there are some issues to study that can be approached in a future work. One of the problems in BSS/ICA algorithms is that sources are estimated within a scale factor and therefore the output are not percentages. It should be desirable to develop a technique to normalize those outputs. Another thing what would be interesting is to quantify the performance of MaxNG for the material percentage estimates, for this purpose it is necessary to have the appropriate dataset where abundances were known in advance.

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