

Spectral unmixing of hyperspectral images with the Independent Component Analysis and wavelet packets

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Abstract – The study addresses the problem of spectral unmixing hyperspectral images, technique allowing the spectra and abundance of each pure material present in each pixel of a scene to be extracted. We first remark that the linear model commonly used in spectral unmixing is exactly the same as the model used in the Independent Component Analysis (ICA), a blind source separation technique studied in the signal processing community. ICA allows each source to be extracted from the observation of some linear combinations of these ones, based on the assumption of their statistical independence. We show the interest of analyzing the spectra issued from a wavelet packets transformation in order to deal with the assumption of independence, which is usually not verified for natural spectra. A pyramidal algorithm is implemented, allowing the problem of the great number of observations to be addressed.

I. INTRODUCTION

Current hyperspectral imaging sensors allow images of natural scenes to be acquired with a great number of spectral bands, from a few to several hundred ones. The spectral domain is then oversampled, unlike multispectral imagery which only enables subsampled reflectance spectra to be acquired. This interesting feature has also a drawback in that the amount of information is too important for standard classification or pattern recognition techniques to be robust. In order to estimate the statistical properties of classes in a supervised classification process, the number of training samples should exponentially increase when the number of dimensions of the data increase. This is not achievable in a real application. However, we can change our point of view and consider the spectra as “true” signals. The amount of information is sufficient to estimate the spectrally purest components of the scene (called endmembers) and the contribution of each one in each pixel. This leads to the spectral mixing model which has been shown to be linear at the scale of observation [1] :

$$M(\lambda) = \sum_{i=1}^n P_i \times R_i(\lambda) \quad (1)$$

with : $M(\lambda)$: Reflectance of a pixel at wavelength λ
 P_i : Proportion of endmember i in the pixel
 $R_i(\lambda)$: Reflectance of endmember i in the pixel
 n : number of endmembers

In order to estimate the proportions for each pixel, the spectra of endmembers should be known. Even if semi-automatic processes can be helpful, this task usually needs the intervention of an expert who should have a very good knowledge of the scene. Having to deal with the great number of spectra to analyze, his task is quite hard. Moreover, pure pixels for each endmember should be present in the scene, which is not still the case. For these reasons, it would be interesting to have an automatic method to determinate the endmembers even if the latter are not purely present in some pixels of the scene. The model (1) can be seen as a special case of Independent Component Analysis (ICA), a blind source separation technique, which has been largely studied these last years by researchers from the signal processing community [2] [3]. ICA allows each source to be automatically extracted from the observation of linear combinations of these sources. In order to retrieve the sources, ICA needs the assumption of statistical independence of the sources. This assumption is unfortunately usually not verified for natural elements reflectance spectra because of the composition of the latter which can be quite the same for different materials. Moreover, ICA is usually used for a few number of sources and observations, typically less than 10, with a great number of samples. In our case, the number of observations is equal to the number of pixels present in the image and can hence be very huge. By opposition, the number of samples is equal to the number of spectral bands and can be very small, especially in the case of sensors who do not have the capability to acquire more than a hundred of spectral bands. We have to face up all these problems in order to apply ICA for spectral unmixing.

II. INDEPENDENT COMPONENT ANALYSIS AND MULTIREOLUTION ANALYSIS

The model of ICA if given by :

$$\mathbf{x} = A \mathbf{s} \quad (2)$$

with : \mathbf{x} : Vector of observed signals
 A : Scalar matrix of mixing coefficients
 \mathbf{s} : Vector of source signals

ICA requires 2 hypothesis :
(H1) : The components s_i of \mathbf{s} are statistically independent.

(H2) : The components s_i of s have non gaussian distributions (It can be shown that no more than one component can be gaussian).

Model (2) implies two non indentifiabilities :

(NI1) : Impossibility of retrieving the variance of the sources (one term a_{ij} of A can be multiplied by a constant and the component s_j of s by the inverse of this constant without changing the model).

(NI2) : Impossibility of retrieving the order of the sources (the order of the components s_i of s and of the lines of the matrix A can be modified without changing the model).

The goal of ICA is to find the matrix $W = A^{-1}$ so that the sources $s_{est} = W x$ can be estimated from the vector x of the observed signals by optimizing a statistical independence criterion. Several algorithms have been proposed for this purpose [4], based on the assumption of the statistical independence of the sources. However, as seen before, the spectra of natural elements are largely correlated and then not statistically independent. It has been recently shown that an auto-regressive (AR) modelisation of the sources can help in capturing their independence while largely filtering their correlation. This idea has been applied for unmixing minerals in hyperspectral images from the AVIRIS sensor [5] [6]. However, the AR modelisation does not seem to be able to capture the independence enough in the case of strongly correlated spectra such as vegetation endmembers in the visible and near infrared part of the electromagnetic spectrum. Moreover, ICA has only been applied to a few pixels [5] or to a few regions [6], not on a whole image.

Authors from the blind source separation community have recently shown that projecting the sources in some suitable base before applying the ICA and using the property of sparsity of the decomposition coefficients largely improves the capability of separation even in the case of correlated sources [7]. Sparsity means that only a few decomposition coefficients differ significantly from zero. We have :

$$s_i(\omega) = \sum_{k=1}^K c_{ik} \times f_k(\omega) \quad (3)$$

with : c_{ik} : coefficients of decomposition

$f_k(\omega)$: base functions

ICA is performed in the domain of coefficients c_{ik} which are able to capture the independence of the sources. The functions $f_k(\omega)$ form a set of given functions and do not need to be linearly independent. A wavelet base decomposition leads to a multiresolution representation of the signals and is well known for providing coefficients with good sparsity properties. Wavelet packets are even better for source separation as they allow the signals to be decomposed in a collection of bases, thus providing more relevant coefficients. The scatterplot of the decomposition coefficients reveals a concentration of points along straight lines in some directions

which are representative of the mixing. If some parts of the signals are independent, some straight lines fall on the axes of the scatterplot. When analyzing signals with wavelet packets, the standard processing step after the decomposition on the whole collection of bases is the choice of the best nodes in the wavelet packets decomposition tree according to a particular criterion. We rather propose to select the best coefficients in all the collection of bases in order to capture the linearities in the scatterplot, related to the local structures of independence in the endmember spectra. ICA can then be applied on the selected coefficients. This method comes to take advantage of the wavelength structure of the spectra for filtering the data before applying a statistical algorithm. Another method consists in estimating the directions of the detected linearities which are the coefficients of the mixing matrix A , i.e. the proportions of each endmember. In opposition to the latter, this method is purely geometric and faster. If the observed spectra are collected in a vector x and the estimated mixing matrix is noted A , then the vector of endmembers s_{est} can be recovered by :

$$s_{est} = A^{-1} x \quad (4)$$

III. ENDMEMBERS RETRIEVAL ALGORITHM

In order to process the whole image, a pyramidal iterative algorithm has been implemented. The strategy of unmixing include the following steps for each level of the pyramide and for each square 3×3 in the level until the level includes only one square :

1/ Interpolate each spectrum present in the square on 2048 samples and make a symetrization of the spectra.

This step does not change the model (2) and allows enough coefficients in the decomposition of next step to be computed as well as numerical problems to be avoided.

2/ Decompose each spectrum in all the nodes of the wavelet packets decomposition tree except the first node at each resolution which contains the lower frequency.

Several mother wavelets are acceptable. A 4 taps Daubechies has been chosen by experimentation. The decomposition has been performed up the 7th level of resolution. A fast decomposition can be implemented with quadrature mirror filters.

3/ Hard-threshold the coefficients to keep only the significative ones.

This step allows too noisy coefficients to be removed and the execution time to be largely reduced. However, it is very interesting to notice that linearities appear at different observation scales of the coefficients. Hence, if the threshold is too high, algorithm will be very fast but only strong linearities will remain. In opposition, a too low threshold will reduce the speed of the algorithm but will allow low level linearities to be detected, the latter corresponding to the presence of an endmember with a small proportion. This is the only parameter of the algorithm allowing the user to

choose a desired compromise between the execution time and detection rate.

4/ Detect the linearities in the scatterplot of the coefficients. A dynamic vector quantization algorithm inspired by the neural gas algorithm [8] and operating at each observation scale has been implemented, allowing lines to be dynamically created when needed, according to a fixed hyperangle φ :

For each observation scale

$t = 0$

Repeat

$t ++$

For each point i of the scatterplot

Determine the closer line d

If no one exists according to φ , create one including i

else rotate d to i : $\Delta\gamma(d,i) = \alpha(t) \times \gamma(d,i)$

with: $\gamma(d,i)$: hyperangle between d and i

$\alpha(t)$: positive monotone decreasing function

EndFor

Until no significant rotations happens

End For

5/ Compute a norm L for each detected linearity and keep only significant linearities.

We built a norm allowing only strong linearities to be kept:

$$L = \Sigma \left(\left\| v_i \right\| \times \left\| v_i \right\|_{\max} \right)^2 \quad (5)$$

With: v_i : vector formed by one point i of the linearity

6/ Fill the proportion estimated matrix A with the normalized coordinates of the detected linearities.

7/ Estimate the endmembers in the square by applying (4) and update the mixing matrix for each pixel at level 0. Reduce the square to one point and keep these endmembers for that point.

IV. RESULTS

The algorithm presented in the last section has been applied to an atmospherically corrected, 2 meters spatial resolution image from the CASI Sensor including only 17 spectral bands from 450 to 950 nm. Fig. 1 shows a part of the original image and the extracted endmembers. Three groups with resembling features corresponding to the three main materials present in the scene can be distinguished. Due to the indetermination of the variance of the sources, only the shape of the endmembers can be recovered. The proportions of each endmember can not be compared between adjacent squares in the image. Normalized recovered endmembers can however be used for standard mean square estimation of proportions in each pixel. Further works will try to integrate spatial information in order to estimate both endmembers and comparable proportions, leading to an unsupervised unmixing process.

CONCLUSION

An automatic procedure for extracting endmembers from hyperspectral imagery has been presented. It allows endmembers to be extracted by sweeping a whole image even from correlated vegetation spectra with a small number of

spectral bands. The compromise between detection rate and execution time is under control. A regularization of the estimation of the proportions needs to be performed in order to recover both endmembers and proportions for each pixel.

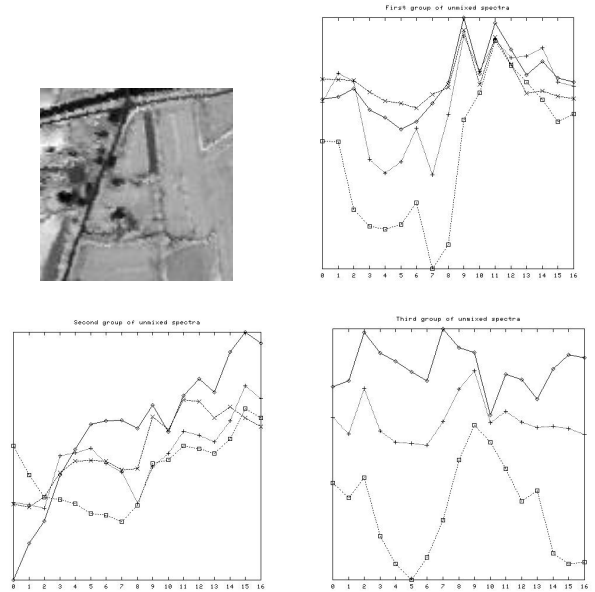


Fig. 1 Image from the CASI and extracted endmembers

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