Linear Unmixing Algorithm Based on Negative Abundance Searching

Applied for Hyperspectral Imaging

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***Abstract*—Hyperspectral linear unmixing is a procedure of decomposing the measured spectrum of an observed scene into a collection of spectral signatures that defines different materials and their corresponding proportions (or abundances) on each pixel of the scene. This procedure consists on three major processes, namely dimension reduction (number of endmembers estimation), endmember extraction, and the abundances estimation. There exist various algorithms for each one of these processes. In this research is proposed a unique algorithm that makes all the hyperspectral linear unmixing.**

Keywords-hyperspectral imaging; linear unmixing; 1-step algorithm; endmembers; abundances; Least Squares Method.

I. INTRODUCTION

In the seventies there were multispectral sensors sensitive to a few dozens of different wavelengths, allowing developing a new paradigm in the material detection and classification.

This classification is based on the fact that all materials reflect, absorb, and emit electromagnetic energy, at specific wavelengths, in distinctive patterns related to their molecular composition [1]. This response dependent on the wavelength is denominated spectral signature, existing a unique spectral signature for each material.

At the beginning of the eighties, the Jet Propulsion Laboratory (JPL) of the National Aeronautics and Space Administration (NASA) developed the Airborne Visible-Infra Red Imaging Spectrometer (AVIRIS) sensor, sensitive to 224 contiguous different wavelengths, from 400 to 2500 nanometers. Furthermore, this sensor allowed overcoming the difficulties that appears when boarding sensors on mobile platforms [2], so it extended the frontier of possibilities offered by this technique.

Remote sensing is one of the possibilities exploited by JPL through AVIRIS sensor. AVIRIS has been flown on four aircraft platforms that fly at approximately 20.000 m above sea level, characterizing a great amount of planet Earth areas. Another remote sensing examples are the two orbiting sensors: Hyperion on the Earth Observing-1 satellite from NASA and CHRIS on the PROBA-1 satellite from European Space Agency (ESA)[3]. In the next three years there will be three more sensors: *Prisma* from the Italian Space Agency (ASI) in 2013 [4], EnMAP from the German Aerospace Center (DLR) and from the German Research Centre for Geosciences (GFZ) in 2015 [5] and also HyspIRI from NASA in 2015[6].

The information collected by sensors is stored in what have been called hyperspectral cubes. Thus, hyperspectral images are modeled as three-dimensional matrices: one dimension reflects the spectral information (wavelengths) and two dimensions reflect the spatial information.

II. BACKGROUND

The spatial resolution, particularly in remote sensing applications, is usually smaller than the size of the objects. This is the reason why there are pixels whose spectral information is a mix of the spectral signatures of different materials.

There are many theoretical models that attempt to explain how the spectral signatures are combined to yield the information contained in the image, most of them based on a linear mixing model such that each pixel can be modeled as a linear combination of a finite number of spectral signatures. These signatures are called endmembers [7].

Hyperspectral unmixing, a procedure of decomposing the measured spectrum of an observed scene into a collection of endmembers and their corresponding proportions (or abundances), is essential in identifying individual materials from a hyperspectral scene.

In hyperspectral unmixing, basically there are three major processes, namely dimension reduction (number of endmembers estimation), endmember extraction, and the abundances estimation. Dimension reduction is useful for complexity reduction of the subsequent endmember extraction and abundance estimation. Principal component analysis (PCA) [8] and maximum noise fraction (MNF) [9] are typical dimension reduction algorithms. However, accurate estimation of the number of dimensions that can truly represent the data space still remains a challenging task, for which some model order estimation methods have been developed, for instance, virtual dimensionality (VD) [10] and hyperspectral signal subspace identification by minimum error (HySime) [11]. Endmember extraction is to determine the endmembers that contribute to the measured spectra. A number of endmember extraction algorithms have been reported, e.g., pixel purity index (PPI) [12], N-finder (N-FINDR) [13], [14], vertex component analysis (VCA) [15], and convex cone analysis (CCA) [16]. Finally, the inversion process is to estimate the abundances associated with the endmember estimates. For instance, fully constrained least squares (FCLS) [17] is an effective algorithm for estimating the abundances.

III. OBJECTIVES

The main objective of the research is the development of an algorithm as a proof of concept, consisting on trying to merge the estimation of the number of endmembers, the endmembers extraction and abundances estimation, forming the entire linear unmixing chain in a 1-step manner. The algorithm is implemented in *Matlab* and is accompanied by a set of tests that provide the results which demonstrate its feasibility.

IV. HYPHOTHESIS

Assuming that the set of endmembers are included in the image as pure pixels, the problem is defined as finding out which combination of p pixels of the image forms the N-dimensional simplex that contains the rest of pixels in it, without knowing p. Moreover, the problem also includes the determination of the abundance of each endmembers in each pixel of the image.

For this purpose, a set of n pixels ($n \leq p$) of the image are initially selected, assuming them as endmembers, i.e., vertices of an N-dimensional simplex. By estimating the abundances of these endmembers in the rest of pixels by Least Squares method, you can determine which pixels are inside and outside the simplex.

Thus, the proposed resolution consists on replacing and adding iteratively the pixels that form the vertices of the simplex, in order to find the combination that includes all the pixels inside. This approach is similar to N-FINDR but replacing the metric, i.e., volume by number of pixels inside the simplex, although N-FINDR is not able to increase the number of vertices of the simplex.

The expected advantage consists on directing the algorithm towards the best candidates to replace the pixels that form the vertices of the simplex, by considering the value of the estimated abundances at each iteration, since the more negative abundance, the better predisposition to be endmember. Furthermore, in this way, pixels which have already been in the interior of one of the successive constructed simplexs during the algorithm can be discarded from search, also allowing increasing the number of endmembers, given the necessity of including all pixels inside the final simplex.

Thus, the algorithm will be able to calculate the number of endmembers, the endmembers and abundances in a unified 1-step algorithm, feeding back the information acquired in the calculation of the abundances. In this manner it is expected to mitigate the influence of errors propagation on subsequent stages. It's important to realize that this approach is just based on spectral information, not taken into account spatial information.

On the other hand, we know that noise distorts the original pixel position in the N-dimensional space, so also it should be necessary to examine how and how much noise affects the approach shown above, also trying to find solutions that allow the algorithm to be robust against noise.

V. EXPERIMENTS

On one hand, it has been defined a synthetic imaging library in order to make the experiments. These images are defined by the number of endmembers (3-21) and by the Signal Noise Ratio (SNR) (40dB, 60dB, 80dB and ∞). On the other hand, it has been defined what have been called a reference chain, that consists of 3 algorithms (VD - VCA - FCLS).

VI. RESULTS

In this section is shown the comparative results obtained for images of size 100x100 pixels, given a set of parameters fixed in the developed algorithm, even when its optimality is not yet studied.

A. *Number of Endmembers Estimation*

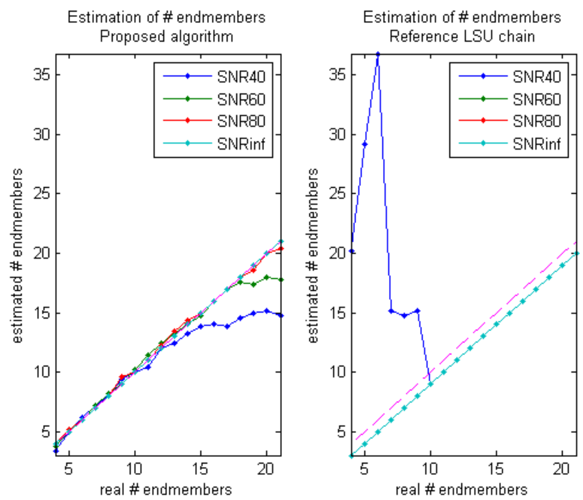

Figure 1. Estimation of # endmembers

.The magenta dashed line shows the line of 45° where the results should be. It is shown how the proposed algorithm without noise makes a perfect estimation of the number of endmembers. However, when noise and the real number of endmembers increase, the algorithm is not able to make a good estimation. Moreover, the reference chain is never able to find the number of real endmembers, always subestimating 1 endmember, except for SNR 40dB, where overestimate.

B. *Endmembers Extraction*

In Figure 2 is shown the spectral angle between n real endmembers and n extracted endmembers, where n is the minimum between the real number of endmembers and the number of estimated endmembers.

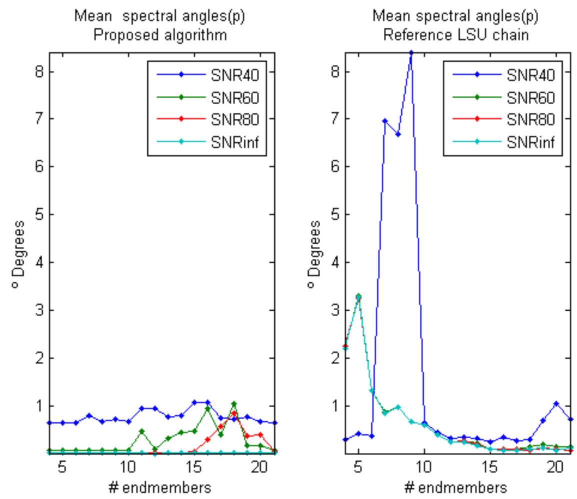

Figure 2. Mean spectral angle

It is shown how the proposed algorithm is very sensitive to noise showing a worse performance when the SNR is 40dB and an excellent performance when there is no noise in the image obtaining angles in the order of 10^{-6}. Moreover, the spectral angles obtained by the reference chain appear insensitive to noise, except in the cases where SNR is 40dB due to the overestimation commented above.

C. *Abundances Estimation*

In Figure 3 is shown the Abundance RMSE for the *n* endmembers shown above.

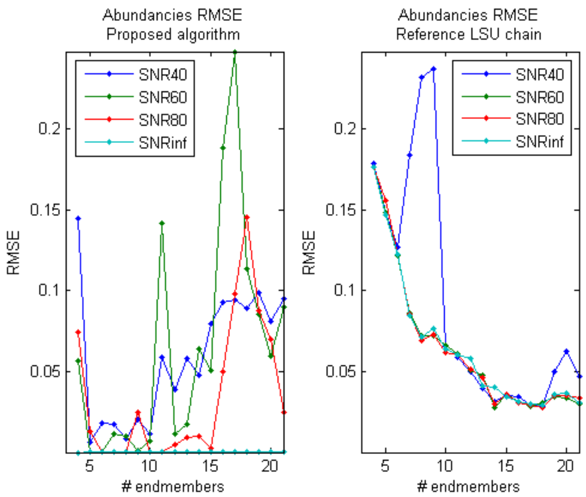

Figure 3. Abundances RMSE

In the same manner, the proposed algorithm shows an extraordinary behaviour in scenarios without noise. However, when SNR decreases, RMSE increases, and also RMSE shows a soft tendency to increase while the real number of endmembers increases, due to a worse estimation of the number of endmembers.

D. *Execution Time*

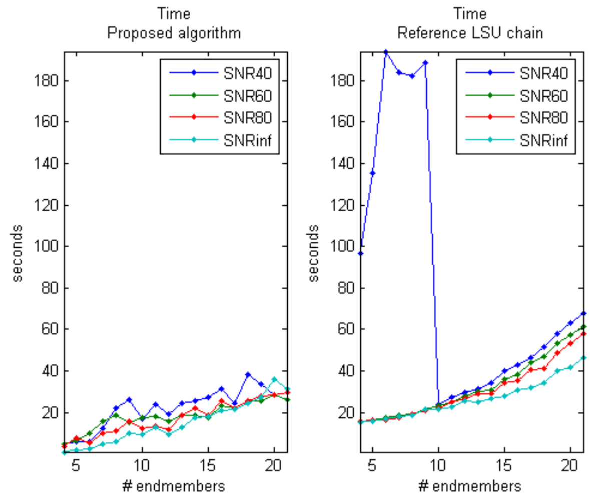

Figure 4. Execution time

As shown in Figure 4, the proposed algorithm is faster than the reference chain for this image size (100x100). The great amount of time that the reference chain exhibits when SNR is equal to 40dB is due to an overestimate of the number of endmembers.

VII. CONCLUSIONS

Given the results shown above, it can be considered to have produced sufficient evidence to conclude that the hypothesis is proved, i.e., the proposed method is functional, showing comparable behavior to a contrasted linear unmixing chain, even when the parameters optimality that defines the algorithm have not been well studied yet.

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