HYPERSPECTRAL UNMIXING WITH SIMULTANEOUS DIMENSIONALITY ESTIMATION

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Abstract: This paper is an elaboration of the simplex identification via split augmented Lagrangian (SISAL) algorithm (Bioucas-Dias, 2009) to blindly unmix hyperspectral data. SISAL is a linear hyperspectral unmixing method of the minimum volume class. This method solve a non-convex problem by a sequence of augmented Lagrangian optimizations, where the positivity constraints, forcing the spectral vectors to belong to the convex hull of the endmember signatures, are replaced by soft constraints.

With respect to SISAL, we introduce a dimensionality estimation method based on the minimum description length (MDL) principle. The effectiveness of the proposed algorithm is illustrated with simulated and real data.

1 INTRODUCTION

Although, there have been significant improvements in the hyperspectral remote sensing sensors, there are in an image pixels than contain more than one material, i.e., the acquired spectral vectors are mixtures of the material spectral signatures present in the scene (Bioucas-Dias and Plaza, 2010; Nascimento and Bioucas-Dias, 2005a).

The linear mixing assumption has been widely used to describe the observed hyperspectral vectors. According to this assumption, a mixed pixel is a linear combination of endmembers signatures weighted by the corresponding abundance fractions. Due to physical considerations, the abundance fractions are subject to the so-called non-negativity and a full-additivity constraints (Bioucas-Dias and Plaza, 2010).

Hyperspectral unmixing, aims at estimating the number of reference materials, also called endmembers, their spectral signatures, and their abundance fractions (Keshava and Mustard, 2002).

Approaches to hyperspectral linear unmixing can be classified as either statistical or geometrical. Statistical methods very often formulate the problem under the Bayesian framework (Nascimento and Bioucas-Dias, 2011; Dobigeon et al., 2009; Arngren et al., 2009; Moussaoui et al., 2008).

The geometric perspective just referred to has been exploited by many algorithms. These algorithms are based on the fact that, under the linear mixing model, hyperspectral vectors belong to a simplex set whose vertices correspond to the endmembers signatures. Therefore, finding the endmembers is equivalent to identifying the vertices of the referred to simplex (Nascimento and Bioucas-Dias, 2005b).

Some algorithms assume the presence of, at least, one pure pixel per endmember (i.e., containing just one material). Some popular algorithms taking this assumption are vertex component analysis (VCA), (Nascimento and Bioucas-Dias, 2005b), the automated morphological endmember extraction (AMEE) (Plaza et al., 2002), the pixel purity index (PPI), (Boardman, 1993), and the N-FINDR (Winter, 1999) (see (Chan et al., 2011) for recently introduced reinterpretations and improvements of N-FINDR). These methods are followed by a fully constrained least square estimation (Heinz and Chein-I-Chang, 2001) or by a maximum likelihood estimation (Settle, 1996) of the abundance fractions to complete the unmixing procedure.

If the pure pixel assumption is not fulfilled, which is a more realistic scenario, the unmixing process is a rather challenging task, since some endmembers are not in the dataset. Some recent methods,
in the vein of Craig’s work minimum Volume Transform (MVT) (Craig, 1994) which finds the smallest simplex that contain the dataset, are the iterated constrained endmember (ICE), (Berman et al., 2004), the minimum volume simplex (MVSA) (Li and Bioucas-Dias, 2008), the Minimum-Volume Enclosing Simplex Algorithm (MVES) (Chan et al., 2009), and the alternating projected subgradients (APS) (Zymnis et al., 2007).

Fig. 1 illustrates three datasets raising different degrees of difficulties in what unmixing is concerned: the dataset shown in Fig.1(a) contains pure pixels, i.e., the spectra corresponding to the simplex vertices are in the dataset. This is the easiest scenario with which all the unmixing algorithms cope without problems; the dataset shown in Fig.1(b) does not contain pure pixels, at least for some endmembers. This is a much more challenging, usually attacked with the minimum volume based methods, note that pure-pixels based methods are outperformed under these circumstances; Fig.1(c), contains a highly mixed dataset where only statistical methods can give accurate unmixing results.

Most of these methods assume that the number of endmembers are known a-priori or estimated for some method, such as, NWHFC (Chang and Du, 2004), HySime (Bioucas-Dias and Nascimento, 2008), and Second moment linear dimensionality (SML) (Bajorski, 2011). The robust signal subspace estimation (RSSE) (Diani and Corsini, 2010) have been proposed in order to estimate the signal subspace in the presence of rare signal pixels, thus it can be used as a preprocessing step for small target detection applications. Sparsity promoting ICE (SPICE) (Zare and Gader, 2007) is an extension of ICE algorithm that incorporates sparsity-promoting priors to find the correct number of endmembers. The framework presented in (Broadwater et al., 2004) also estimates the number of endmembers when it unmix the data. This framework has the disadvantage of using the Unsupervised Fully Constrained Least Squares (UFCLS) algorithm proposed in (Heinz and Chein-I-Chang, 2001) which assumes the presence of at least one pure pixel per endmember.

Simplex identification via split augmented Lagrangian (SISAL) (Bioucas-Dias, 2009) belongs to the minimum volume class methods. The non-convex optimization problem is solved as a sequence of non-smooth convex subproblems using variable splitting to obtain a constraint formulation, and then applying an augmented Lagrangian technique.

This paper proposes an improvement of SISAL by introducing an algorithm based on the minimum description length (MDL) principle. Thus, SISAL is able to estimate the number of endmembers as it unmix the hyperspectral dataset.

This paper is organized as follows. Section 2 describes the fundamentals of the proposed method. Section 3 presents the method to infer the number of number of endmembers. Section 4 illustrates as-
pects of the performance of the proposed approach
with experimental data based on U.S.G.S. laboratory
spectra and with real hyperspectral data collected by
the AVIRIS sensor, respectively. Section 5 concludes
with some remarks.

2 PROBLEM FORMULATION

Assuming the linear observation model, each pixel
y of an hyperspectral image can be represented as a
spectral vector in \( \mathbb{R}^l \) (\( l \) is the number of bands) and is
given by \( y = Ms + n \), where \( M = [m_1, m_2, ..., m_p] \) is
an \( l \times p \) mixing matrix (\( m_i \) denotes the \( i^{th} \) endmem-
ber spectral signature), \( p \) is the number of endmem-
ers present in the covered area, \( s = [s_1, s_2, ..., s_p]^T \) is
the abundance vector containing the fractions of each
endmember (notation \( \cdot^T \) stands for vector trans-
posed), and vector \( n \) holds the sensor noise and mod-
ing errors.

To fix notation, let \( Y = [y_1, ..., y_n] \in \mathbb{R}^{l \times n} \) denote
a matrix holding the observed spectral vectors, \( S =
[s_1, ..., s_n] \in \mathbb{R}^{p \times n} \) a matrix holding the respective
abundance fractions, and \( N = [n_1, ..., n_n] \in \mathbb{R}^{n \times n} \)
accounts for additive noise. To be physically meaning-
ful, abundance fractions are subject to non-negativity
and constant sum constraints, \( \{s \in \mathbb{R}^n : s \succeq 0, 1_p^T s = 1_p^T \} \). Therefore

\[
Y = MS + N
\]

s.t. \( S \succeq 0, 1_p^T S = 1_p^T. \) (1)

Usually the number of endmembers is much lower
than the number of bands (\( p \ll L \)). Thus, the observed
spectral vectors can be projected onto the signal
subspace. The identification of the signal subspace im-
proves the SNR, allows a correct dimension reduc-
tion, and thus yields gains in computational time and
complexity (Bioucas-Dias and Nascimento, 2008).

Let \( E_p \) be a matrix, with orthonormal columns,
spanning the signal subspace. Thus

\[
X = E_p^T Y + E_p^T N = AS + N',
\]

where \( X = [x_1, ..., x_n] \in \mathbb{R}^{p \times n} \) denote a matrix hold-
ing the projected spectral vectors, \( A = E_p^T M \) is a \( p \times p \)
Square mixing matrix, and \( N' \) accounts for the pro-
jected noise.

Linear unmixing amounts to infer matrices \( A \) and
\( S \). This can be achieved by fitting a minimum volume
simplex to the dataset (Craig, 1994). Finding a mi-
mimum volume matrix \( A \) subject to constraints in (1),

\[ 1^T s \succeq 0 \text{ means } s_j \geq 0, \text{ for } j = 1, ..., p \text{ and } 1_p^T \equiv [1, ..., 1] \]

leads to the non-convex optimization problem

\[
\hat{Q} = \arg \min_Q \{ - \log |\det Q| \}
\]

s.t. \( QX \succeq 0, 1_p^T QX = 1_p^T, \) (3)

where \( Q \equiv A^{-1} \). The constraint \( 1_p^T QX = 1_p^T \) can
be simplified, by multiplying the equality on the right
hand side by \( X^T (XX^T)^{-1} \), resulting in \( 1_p^T QX = 1_p^T \Rightarrow
1_p^T Q = a^T \), where \( a^T \equiv 1_p^T X^T (XX^T)^{-1}. \)

SISAL aims to give a sub-optimal solution of (3) solving
the following problem by a sequence of aug-
mented Lagrangian optimizations:

\[
\hat{Q} = \arg \min_Q \{ - \log |\det Q| + \lambda \|QX\|_h \}
\]

s.t. \( 1_p^T Q = a^T, \) (4)

where \( \|QX\|_h = \sum_i h(QX) \), \( h(x) \equiv \max(-x, 0) \) is
the so-called hinge function and \( \lambda \) is the regulariza-
tion parameter. Notice that \( \|QX\|_h \) penalizes nega-
tive components of \( QX \), thus playing the rule of a
soft constraint, yielding solutions that are robust to
outliers, noise, and poor initialization.(see (Bioukas-
Dias, 2009) for details).

3 NUMBER OF ENDMEMBERS

ESTIMATION

The MDL principle proposed by Rissanen (Rissanen,
1978) aims to select the model that offers the shortest
description length of the data. This approach can be
used to estimate the number of endmembers (Broad-
water et al., 2004). The well-known MDL criterion
for \( n \) i.i.d. observations, in general, is given by

\[
\hat{k}_{\text{MDL}} = \arg \min_k \left\{ L(\hat{X} | \hat{\theta}_k) + \frac{1}{2} k \log n \right\},
\]

where \( L(\hat{X} | \hat{\theta}_k) \) is a likelihood equation based on the
projected data \( X \) with parameters \( \theta \), and \( \frac{1}{2} k \log n \) is
the penalizing term that increases with \( k \) (Figueiredo
and Jain, 2002).

Assuming that the additive noise is Gaussian dis-
tributed, \( \sim \mathcal{N}(0, \Lambda) \) and given a set of \( n \) i.i.d.
observerd samples, the likelihood equation is given by:

\[
L(\hat{X} | \hat{\theta}_k) = \sum_{i=1}^{n} \left[ - \log p(x_i | \hat{\theta}_k) \right]
\]

\[
= \frac{1}{2} \left[ (X - AS)^T \Lambda^{-1} (X - AS) \right] + \frac{1}{2} \text{tr} \left[ (X - AS)^T \Lambda^{-1} (X - AS) \right],
\]

(6)
4 EXPERIMENTS

This section provides simulated and real data experiments to illustrate the algorithm's performance. The proposed method is tested and compared with SPICE (Zane and Gader, 2007) on different simulated scenarios concerning with different signal-to-noise ratio (SNR), absence of pure pixels, and number of endmembers present in the scene. The proposed method is also applied to real hyperspectral data collected by the AVIRIS sensor over Cuprite, Nevada.

4.1 Evaluation with Simulated Data

In this section the proposed method is tested on simulated scenes. To evaluate the performance of the algorithm the spectral angle distance (SAD) (Keshava and Mustard, 2002) is used. This widely known metric measures the shape similarity between the \( \hat{\mathbf{m}}_i \) and its estimate \( \hat{\mathbf{m}}_i \). Based on this metric we define a spectral root mean square angle error, given by:

\[
e_m \equiv \frac{1}{p} \left[ \sum_{i=1}^{p} \left( \arccos \frac{\mathbf{m}_i^T \hat{\mathbf{m}}_i}{||\mathbf{m}_i|| ||\hat{\mathbf{m}}_i||} \right)^2 \right]^{1/2}.
\]

To measure the similarity between the observed data and the unmix result it is also computed the residual error between the observed pixels and their estimates:

\[
r_{ls} \equiv ||\mathbf{Y} - \hat{\mathbf{M}}\hat{\mathbf{S}}||_F^2.
\]

Concerning the simulated data creation a hyperspectral image composed of \( 10^4 \) pixels is generated according to expression (1), where spectral signatures where selected from the USGS digital spectral library. The selection of endmember signatures is arbitrary as long as they are linearly independent. The reflectances contain 224 spectral bands covering wavelengths from 0.38 to 2.5 \( \mu \text{m} \) with a spectral resolution of 10 nm. The abundance fractions are generated according to a Dirichlet distribution given by

\[
D(s_1, \ldots, s_p | \mu_1, \ldots, \mu_p) = \frac{\Gamma(\sum_{j=1}^{p} \mu_j)}{\prod_{j=1}^{p} \Gamma(\mu_j)} \prod_{j=1}^{p} s_j^{\mu_j - 1},
\]

where \( \{s_1, \ldots, s_p\} \) are subject to non-negativity and constant sum constraints. This density, besides enforcing positivity and full additivity constraints, displays a wide range of shapes, depending on the parameters of the distribution \( \mu = [\mu_1, \ldots, \mu_p] \). In this experiment the Dirichlet parameters are set to \( \mu = [3, \ldots, 3] \), concerning the additive noise, the SNR, which is defined as \( \text{SNR} \equiv 10 \log_{10} \left( \frac{\mathbb{E}\{\mathbf{y}^T \mathbf{y}\}}{\mathbb{E}\{\mathbf{n}^T \mathbf{n}\}} \right) \), is set to 30 dB.

Fig. 2 presents a scatterplot of the simulated scene for the \( p = 3 \) case, where dots represent the pixels and circles represent the true endmembers. This figure also shows the endmembers estimates (squares). Fig. 3 shows the endmembers signatures (solid line) and their estimates (dashed line). Note that, in this experiment there is no pure pixels in the dataset, however, the endmembers estimates are very close to the true ones.

Fig. 4 presents the evolution of the cost function [see expression (5)] as a function of the number of endmembers. The minimum of the function occurs at \( k = 3 \) which is the true number of endmembers in the scene.

Table 1 presents the root mean square error distance \( e_m \), the residual least squares error \( r_{ls} \), and the estimated number of endmembers for different experiments where \( p \) is set to \( \{3, 5, 10\} \) and the SNR is set to \( \{30, 50\} \) dB. Note that the estimated values are exactly the number of endmembers in the scene and...
Figure 3: Endmembers signatures (solid line) and their estimates (dashed line).

Figure 4: Cost function evolution as a function of the number of endmembers.

Table 1: Results for different scenarios as a function of the SNR and of the number of endmembers ($p$).

<table>
<thead>
<tr>
<th>SNR</th>
<th>$p$</th>
<th>Proposed Method</th>
<th>SPICE</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$k$</td>
<td>$\hat{e}_m$</td>
<td>$r_{ls}$</td>
</tr>
<tr>
<td>30dB</td>
<td>3</td>
<td>0.048</td>
<td>4.76</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>0.053</td>
<td>6.41</td>
</tr>
<tr>
<td></td>
<td>10</td>
<td>0.299</td>
<td>7.18</td>
</tr>
<tr>
<td>50dB</td>
<td>3</td>
<td>0.042</td>
<td>0.47</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>0.059</td>
<td>0.64</td>
</tr>
<tr>
<td></td>
<td>10</td>
<td>0.196</td>
<td>1.70</td>
</tr>
</tbody>
</table>

The unmix error increases with increasing values of $p$ and with noise level. The results achieved by SPICE in terms of residual error are similar to the proposed method results, although the errors between endmembers signatures and their estimates are worst.

Table 2: Results for Cuprite dataset.

<table>
<thead>
<tr>
<th>Proposed method</th>
<th>SPICE</th>
</tr>
</thead>
<tbody>
<tr>
<td>$k$</td>
<td>6</td>
</tr>
<tr>
<td>$r_{ls}$</td>
<td>7</td>
</tr>
</tbody>
</table>

4.2 Experiments with Real Hyperspectral Data

In this section, the proposed method is applied to a subset ($50 \times 90$ pixels and 224 bands) of the Cuprite dataset acquired by the AVIRIS sensor on June 19, 1997. Fig. 5 shows band 30 (wavelength $\lambda = 655.8 \text{nm}$) of the subimage of AVIRIS Cuprite Nevada dataset (rectangle denotes the image fraction used in the experiment).

In this section, the proposed method is applied to a subset ($50 \times 90$ pixels and 224 bands) of the Cuprite dataset acquired by the AVIRIS sensor on June 19, 1997. Fig. 5 shows band 30 (wavelength $\lambda = 655.8 \text{nm}$) of the subimage of AVIRIS Cuprite Nevada dataset. The AVIRIS instrument covers the spectral region from 0.41 $\mu$m to 2.45 $\mu$m in 224 bands with a 10nm band width. Flying at an altitude of 20 km, it has anIFOV of 20 m and views a swath over 10 km wide. This site has been extensively used for remote sensing experiments over the past years and its geology was previously mapped in detail (Swayze et al., 1992).

Table 2 present the residual error and the estimated number of endmembers for SPICE and for the proposed method. The results of both methods are comparable.

Fig. 6 shows the estimated signatures, which are compared with the nearest laboratory spectra, to visually distinguish the different endmembers an offset has been added to each signature. Note that, this endmembers are known to dominate the considered subimage (Swayze et al., 1992).
5 CONCLUSIONS

In this paper, a new method is proposed to blindly unmix hyperspectral data and simultaneously infer the number of endmembers based on the minimum description length (MDL) principle. The endmembers spectra estimates is based on SISAL algorithm (Bioucas-Dias, 2009) which solves a non-convex problem by a sequence of augmented Lagrangian optimizations. The experimental results achieved shows the potential of the proposed method.

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