INTEGRATING ANOMALY DETECTION TO SPATIAL PREPROCESSING FOR ENDMEMBER EXTRACTION OF HYPERSPECTRAL IMAGES

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ABSTRACT
Spectral unmixing is the process of identifying pure spectral signatures, called endmembers, from a hyperspectral data, and then expressing each pixel vector in terms of the fractional abundances of these endmembers. Most of the endmember extraction methods in the literature use only the spectral information, whereas the spatial composition of the data is disregarded. Spatial preprocessing methods, that are motivated by the assumption that endmembers are more likely to be located in homogeneous regions instead of transition areas, can alleviate this drawback and hence increase the performance. However, such a preprocessing approach generally results in a failure of extracting anomalous endmembers which can be of importance for many applications. In this paper, a preprocessing approach that guides the endmember extraction process to homogeneous regions while retaining the anomaly points, by combining spatial preprocessing with anomaly detection, is proposed.

Index Terms— Anomaly detection, endmember extraction, hyperspectral imaging, spatial preprocessing

1. INTRODUCTION

Hyperspectral imaging provides data acquired in hundreds of spectral channels, with higher spectral resolution than multispectral images. This high content of spectral information results in an increased capability of classification and detection for hyperspectral images with respect to standard imaging systems [1]. However, many of such image processing tasks operate with the assumption that each pixel vector is the response of a single underlying material. In the cases that the spatial resolution of the hyperspectral sensor is not high enough to accurately distinguish different materials, or when intimate mixtures occur, the response of a pixel vector is comprised of a mixture of different spectral signals.

Unmixing is the process of representing the mixed pixels in terms of fractional abundances of pure spectral signals, named as endmembers [2]. There are a large number of endmember extraction algorithms (EEAs) in the literature, among which N-FINDR [3], vertex component analysis (VCA) [4], and orthogonal subspace projection (OSP) [5] are just some of the many. Most of these EEAs rely solely on the spectral properties of the data, without giving heed to spatial distribution [6]. Spatial preprocessing techniques that are motivated by the idea that spectrally pure signatures, i.e. endmembers, are more likely to be encountered in spatially homogeneous regions instead of transition areas, and aim to direct the endmember extraction process to spatially homogeneous regions, may increase the performance of EEAs [6-7]. However, such an approach results in a failure of detecting anomalous endmembers, by this guidance to homogenous regions [6].

Anomaly detection is an unsupervised automatic target detection approach that aims to detect pixels which are significantly different with respect to surrounding pixels i.e. are anomalous with respect to the background. No a priori information on the anomalies is required and the anomalies of interest may range from crop stress locations or rare minerals to man-made objects [8]. Reed-Xiaoli (RX) algorithm [9] is the benchmark anomaly detection method in the literature and is a constant false-alarm rate (CFAR) adaptive method based on generalized likelihood test. RX has been applied to hyperspectral images in [10]. Kernel RX (KRX) [11] is a nonlinear version of RX that uses the kernel trick to better exploit the higher order correlation of the spectral bands of a hyperspectral data.

In this paper, region-based spatial pre-processing (RBSPP) [4] is combined with KRX anomaly detection as a preprocessing step to endmember extraction of hyperspectral images. This two-way approach guides the endmember extraction process to spatially homogenous regions while retaining anomalies, hence provides increased performance while preserving the anomalous endmembers. The proposed approach can be used priory to any spectral-based EEA.

2. RBSPP

RBSPP is motivated by the assumption that endmembers are more likely to be located in homogenous regions, and selects a subgroup of pixel vectors from homogenous regions to be
used as input to the endmember extraction, instead of the whole data.

RBSSPP starts with an unsupervised segmentation step, which is used to partition the data into spatial clusters of spectrally similar content. Then, OSP is applied to the mean spectra of each cluster, to select a subset of spatial regions that are spectrally distinct and orthogonal. OSP starts this process by selecting the first region as the region with the highest intensity mean spectra.

\[
R_t = \arg\left\{ \max_l \sum_{i=1}^L M_i^t M_i^t \right\}
\]

(1)

where \(M_i\) is the mean spectra of region \(l\), and \(r\) is the number of regions. Once \(R_t\) is identified, the algorithm assigns \(U_t = [R_t]\). Then, the algorithm iteratively continues to apply OSP to the mean spectra of each remaining region to select the next region with the maximum projection of its mean spectra to the mean spectra of already selected regions, starting with \(U_2 = [R_1, R_2]\), obtained from:

\[
R_2 = \arg\left\{ \max_l \left[ \left( P_{U_1}^t M_l \right)^T \left( P_{U_1}^t M_l \right) \right] \right\}, \quad \text{with} \quad P_{U_1}^t = I - U_1(U_1^T U_1)
\]

(2)

where \(I\) is the identity matrix. The algorithm stops these iterations when a predefined number of regions have been selected.

3. RX & KRX

RX estimates a background model for the data as a Gaussian distribution with zero mean and an unknown covariance matrix. Based on this background model, a sliding window is used for local demeaning and to enforce the local Gaussian assumption. Anomaly detection is conducted by calculating the Mahalanobis distance between a tested pixel vector and the background model:

\[
RX(r) = (r - \hat{\mu}_b)^T \hat{C}_b^{-1} (r - \hat{\mu}_b)
\]

(3)

where \(r\) is the tested pixel vector, and \(\mu_b\) and \(C_b\) are the estimated background mean vector, and covariance matrix, respectively. The resulting RX values are compared to a threshold to determine whether the tested pixel vector is an anomaly.

KRX is a nonlinear version of RX, which exploits the nonlinear relationships between the spectral bands of a hyperspectral image [11]. In addition, the local Gaussian background assumption is more valid in higher-dimensional space [11]. KRX is implemented without a requirement of explicit knowledge of the nonlinear mapping function, by using the kernel trick, resulting in the following equations [11]:

\[
KRX(r) = (K_r^T - K_{\hat{\mu}_b})^T \hat{K}_b^{-1} (K_r^T - K_{\hat{\mu}_b})
\]

(4)

\[
K_r^T \equiv k(X_b, r)^T - \frac{1}{M} \sum_{i=1}^M k(x(i), r)
\]

(5)

\[
K_{\hat{\mu}_b}^T \equiv \frac{1}{M} \sum_{i=1}^M k(x(i), X_b) - \frac{1}{M^2} \sum_{i=1}^M \sum_{j=1}^M k(x(i), x(j))
\]

(6)

\[
\hat{K}_b^{-1} = \frac{1}{M} B\Lambda_b^{-1} B^T
\]

(7)

where \(A_b\) is the diagonal eigenvalue matrix and \(B\) is the eigenvector matrix of the centered kernel matrix normalized by the square root of corresponding eigenvalues.

KRX generally yields fewer false alarms than RX. However, it has a higher computational burden due to the calculation and inversion of Gram matrices.

4. PROPOSED METHOD

The proposed method can be summarized as follows:

1) The number of endmembers in the hyperspectral data is determined using Harsanyi-Farrand-Chang method (HFC) [12] in this paper.

2) RBSSPP is applied to the data. ISODATA [13] is used in this paper for the unsupervised segmentation step. The minimum number of regions for ISODATA is selected as the number of endmembers in the image, and the maximum number of regions is selected as two times this number. The number of regions resulting from OSP is selected as the number of endmembers.

3) KRX anomaly detection is applied to the data in parallel to the previous step. A Gaussian radial basis function (RBF) kernel is used. Kernel window size is selected as 15 x 15 as compensation between performance and computation time. Threshold value is selected as 0.7.

4) The pixel vectors resulting from RBSSPP and the anomalous pixel vectors resulting from KRX are given as input to an EEA. In this paper, VCA is used as the EEA.

5. EXPERIMENTAL RESULTS ON SYNTHETIC DATA

A synthetic hyperspectral data of 100×100 pixels and 221 spectral bands was used to test the performance of the proposed approach. This data, labeled “Fractal 1”, provides a spatial pattern that is often found in nature [6]. This data contains 9 mineral signatures, as endmembers, from U.S. Geological Survey (USGS) spectral library, namely Kaolinite KGa1, Dumortierite, Nontronite, Alunite, Sphene, Pyrophilite, Halloysite, Muscovite, and Kaolinite CM9 minerals. The endmember spectral signatures of the data can be observed in Fig. 1.
The performance of the proposed method is evaluated for two cases, namely when the hyperspectral data does and does not contain anomalies. To test the performance of the proposed approach on data that contains anomalies, two anomaly signatures which are selected from USGS spectral library, namely Dark Red Building Brick, and Metal Sheet, are injected to the synthetic data, in the size of one pixel vector each. The spectral signatures for the anomalous endmembers are presented in Fig. 2.

Zero-mean Guassian noise is added to the data in different signal-to-noise ratios (SNRs) to observe the robustness of the methods against noise. The evaluation is carried out in terms of spectral angular distance (SAD), which enables us to observe how close the extracted endmembers are to the endmembers used in the synthetic data. SAD scores are provided in Table 1 and Table 2.

![Fig. 2: Anomaly signatures](image)

### Table 1: SAD scores for the data without anomalies

<table>
<thead>
<tr>
<th>Preprocess</th>
<th>10dB SNR</th>
<th>30dB SNR</th>
<th>50dB SNR</th>
</tr>
</thead>
<tbody>
<tr>
<td>-</td>
<td>0.0632</td>
<td>0.0566</td>
<td>0.0575</td>
</tr>
<tr>
<td>RBSPP</td>
<td>0.0807</td>
<td>0.0752</td>
<td>0.0732</td>
</tr>
<tr>
<td>RBSPP + KRX</td>
<td>0.0805</td>
<td>0.0777</td>
<td>0.0732</td>
</tr>
</tbody>
</table>

### Table 2: SAD scores for the data with anomalies

<table>
<thead>
<tr>
<th>Preprocess</th>
<th>10dB SNR</th>
<th>30dB SNR</th>
<th>50dB SNR</th>
</tr>
</thead>
<tbody>
<tr>
<td>-</td>
<td>0.1256</td>
<td>0.1173</td>
<td>0.1456</td>
</tr>
<tr>
<td>RBSPP</td>
<td>0.1214</td>
<td>0.1001</td>
<td>0.0956</td>
</tr>
<tr>
<td>RBSPP + KRX</td>
<td>0.1208</td>
<td>0.0715</td>
<td>0.0783</td>
</tr>
</tbody>
</table>

It can be observed from Table 1, that the proposed method does not result in a significant degradation of performance when no anomalies are present in the data. Although some false alarms may be unavoidable, the pixel vectors resulting from KRX are a small number and hence do not degrade the performance significantly. It should also be noted that RBSPP has not provided an increased endmember extraction performance for this data with respect to standard VCA, which results in standard VCA performing better than the proposed approach.

However, when anomalies are present, as can be observed from Table 2, the proposed approach further improves the performance obtained using RBSPP prior to VCA, and the improvement is significant. Visual results on the extracted endmember locations are provided in Fig. 3, for 30dB SNR.

### 6. EXPERIMENTAL RESULTS ON REAL DATA

AVIRIS Salinas data, of 512 x 217 pixels and 224 spectral bands, is used to test the performance of the proposed approach on real hyperspectral data. AVIRIS Salinas dataset already contains an anomaly and some buildings that can be considered anomalous. The results are provided only visually, since there is no conclusive information on the endmember signatures contained in the Salinas dataset. The visual results are provided in Fig. 4. It can be observed that the proposed approach results in endmembers being selected from homogenous regions and anomalous pixel vectors.

### 7. CONCLUSIONS

In this paper, a preprocessing approach that combines the properties of spatial processing and anomaly detection for hyperspectral images is proposed. The proposed approach guides the endmember extraction process to spatially homogeneous regions by RBSPP while also retaining anomalies detected by KRX as candidate anomalous endmembers. Experimental results demonstrate the promising performance of the proposed approach on both synthetic and real data. The proposed approach is fit to be used prior to any spectral-based EEA, and does not require any modification is the extraction process.

### 8. ACKNOWLEDGEMENT

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9. REFERENCES


Fig. 3: Visual results for Fractal 1 data, with 30dB SNR Gaussian noise and two anomalies. (a) Endmember locations by VCA. (b) RBSP regions. (c) Endmember locations by VCA after RBSP. (d) Anomaly locations. (e) Endmember locations by VCA after KRX and RBSP.

Fig. 4: Visual results for AVIRIS Salinas data. (a) Endmember locations by VCA. (b) RBSP regions. (c) Endmember locations by VCA after RBSP. (d) Anomaly locations. (e) Endmember locations by VCA after KRX and RBSP.