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Efficient Clustering-based Noise Covariance Estimation for Maximum Noise Fraction

Soumyajit Gupta and Chandrajit Bajaj

University of Texas at Austin, Austin TX 78705, USA

Abstract

Most hyperspectral images (HSI) have important spectral features in specific combination of wave numbers or channels. Noise in these specific channels or bands can easily overwhelm these relevant spectral features. Maximum Noise Fraction (MNF) by Green *et al.* [1] has been extensively studied for noise removal in HSI data. The MNF transform maximizes the Signal to Noise Ratio (SNR) in feature space, thereby explicitly requiring an estimation of the HSI noise. We present two simple and efficient Noise Covariance Matrix (NCM) estimation methods as required for the MNF transform. Our NCM estimations improve the performance of HSI classification, even when ground objects are mixed. Both techniques rely on a superpixel based clustering of HSI data in the spatial domain. The novelty of our NCM's comes from their reduced sensitivity to HSI noise distributions and interference patterns. Experiments with both simulated and real HSI data show that our methods significantly outperforms the NCM estimation in the classical MNF transform, as well as against more recent state of the art NCM estimation methods. We quantify this improvement in terms of HSI classification accuracy and superior recovery of spectral features.

Keywords

Hyperspectral image; Maximum noise fraction; Noise covariance estimation; Superpixel; Classification

1 Introduction

The emergence and development of hyperspectral (HS) remote sensing technology has made it possible to acquire data with large amounts of spatial and spectral information for image analysis applications such as classification, unmixing, subpixel mapping, and target detection [2]. HS imaging is applicable to a wide variety of fields, including agriculture, environment, mineral mapping, surveillance, and chemical imaging of biological tissue [3,4]. The acquired hyper spectral images (HSI) are often disturbed by radiometric noise such as sensor noise, photon (or shot) noise, calibration error, atmospheric scattering and

Correspondence to: Chandrajit Bajaj.

Soumyajit Gupta [0000-0001-8145-9347]

Chandrajit Bajaj [0000-0002-9619-3278]

absorption, which not only degrades the visual quality but also the final HSI analysis or interpretation via image classification techniques. The various aforementioned HSI noise is generally represented as an additive normally distributed (Gaussian), zero-mean random process [5].

It was shown by Green *et al.* [1] that the variance of hyperspectral images did not necessarily reflect the real SNR, due to unequal noise variances in different channels or bands, with noise variance dominating the signal variance in some bands. As a result, a band with small variance does not necessarily mean poor image quality. It may have a high SNR compared to other bands with large variances but low SNR's. In order to deal with this problem, Green *et al.* [1] developed the Maximum Noise Fraction (MNF) transform based on maximization of SNR, so that the transformed principal components are ranked by SNR rather than variance as used in PCA.

One of the major disadvantages of this approach is that the Noise Covariance Matrix (NCM) must be estimated completely and accurately from the data apriori. This is generally difficult to do so, due to the stochastic nature of noise, and as pointed out in [1, 6]. Several papers have been done to address this issue by considering the neighboring spatial information [7, 8], as well as jointly considering neighborhood spatial and spectral information [9, 10], leading to high complexity algorithms just for the NCM estimation.

Our main contributions are two-fold. First, we present a simple method to generate a panchromatic image from the HSI. Second, we propose two variants of NCM estimation approaches (neighborhood and cluster) based on the fast superpixel [11] SLIC algorithm. They depend only on the spatial information of the generated image, and can effectively recover a good estimate of the NCM, achieving good classification scores after MNF denoising. Being spatial based, they have lower computation cost (proportional to the number of pixels in the HSI), compared to spectral based methods. Our results, as demonstrated below, significantly outperforms both the spatial and spectral based approaches in terms of classification accuracy and recovery of spectral features. Both our algorithms remain unaffected with the scaling of the data in terms of size, hence provides a better NCM estimation for large datasets.

2 Theory

2.1 Notation

We are given a HSI $Y_{orig} \in \mathbb{R}^{W \times H \times S}$, where W, H are the spatial dimensions (width, height) and S is the number of spectral channels. It can be restructured/vectorized into a 2D matrix $Y \in \mathbb{R}^{N \times S}$, where $N = (W \times H)$ is the number of pixels. Each column $y_i, \forall i = [1 : S]$ represents the reshaped image for the i -th spectral channel and each row $y_j, \forall j = [1 : N]$ represents the spectral signature for the j -th pixel.

2.2 Related Work

The main difference between conventional PCA and MNF is that: MNF has a prior step of noise whitening, which needs a good estimate of the NCM. The original MNF method

mainly adopts the spatial feature of image to estimate $\Sigma_{\mathcal{S}}$, such as minimum/maximum autocorrelation factor (MAF) by Switzer and Green [7], causal simultaneous autoregressive and quadratic surface by Nielsen [8].

As shown in studies by Roger [12], Greco *et al.* [13] and Liu *et al.* [9], spatial-based noise estimation method is data-selective and unstable. When HSI has low spatial resolution, the difference between pixels may mainly contain signal. Sometimes, noise with regular (interference) pattern may be considered as signal when spatial features are used in NCM estimation. When the structure/distribution of the noise is unknown, such methods always fall short in estimating $\Sigma_{\mathcal{S}}$.

In HSI there exists correlation between channels. Therefore, high correlations between channels can also be used for noise estimation, as in Liu *et al.* [9] by using both spatial and spectral domain information. The signal value of current pixel at a channel is estimated from the value of adjacent channels of the same pixel and adjacent pixels in the same channel, through multiple linear regression. Then difference between the estimated signal value and the raw value of the current pixel, is considered as noise.

The work of Optimized MNF by Gao *et al.* [10] extends the idea of Liu *et al.* [9] by computing noise over small non-overlapping sub-blocks locally, thereby further reducing the influence of spatial features. They solve multiple linear analysis over each sub-block to compute the residual noise, followed by computing the local standard deviation (LSD) for each of those sub-blocks, and binning those values over the range of computed LSD.

2.3 Superpixel

A superpixel is defined as a group of pixels having similar characteristics. We consider the Simple Linear Iterative Clustering (SLIC) superpixel of Achanta *et al.* [11]. It generates superpixels by clustering pixels based on their color similarity and proximity in the image plane. This is done in the five-dimensional $[labxy]$ space, where $[lab]$ is the pixel color vector in CIELAB color space, which is widely considered as perceptually uniform for small color distances, and $[xy]$ is the spatial pixel position.

We use the SLICO¹ (the zero parameter optimized version of the SLIC algorithm) version, which adaptively chooses the compactness parameter for each superpixel differently, generating regular shaped groups in both textured and non textured regions alike, and can be used on grayscale and color images. The cost is $O(N)$, hence computationally efficient and real time.

3 Effect of mixing of pixels on NCM

Green *et al.* [1] uses the Maximum Autocorrelation Factor (MAF) [7] transform to obtain $\Sigma_{\mathcal{S}}$:

¹Code available at: <http://ivrl.epfl.ch/research/superpixels>

$$\sum_{\delta} = \frac{1}{2} \text{Cov}(Y_{j,i} - Y_{j+\Delta,i}) \quad (1)$$

where Δ denotes spatial shift in pixel. In Eq.1, the subtractions between neighboring pixels is performed to estimate $\sum_{\delta}$. If the spatial distribution of ground objects keeps getting complex as shown in Fig. 2, NCM estimates are very bad, hence classification results after MNF transform will be seriously affected as shown in Fig. 3, due to bad estimation of noise from pixels from different classes. In such scenarios, neighbors of each pixel would vary depending on the vectorization format (row or column wise), leading to poor noise estimation.

4 Spectral based approaches

Spectral approaches are state of the art in terms of Effective noise estimation but time consuming. We ran the same experiment using Optimized MNF of Gao *et al.* [10], which considers noise estimation in the HSI cube, hence unaffected by vectorization of the data during MNF. Firstly, solving the system of regression for each pixel of each channel takes huge memory and time. Secondly, depending on the spectrum, this method at times becomes numerically unstable, which results in degraded noise estimation. This Effect is clearly illustrated in Fig. 4, where at the first level the classification is fair. However, at subsequent levels, due to mixing of objects the regression solver suffers from being badly scaled and close to singular. This happens due to pixels from multiple materials participating in determining the noise level of a pixel from different class.

5 Generating Panchromatic image for SLIC

A HSI contains large number of continuous spectral bands with narrow bandwidth. To extract spatial features in a fast and simple way, we use a synthesized panchromatic image inspired by the work in Zhang *et al.* [15]. This generated panchromatic image $I \in \mathbb{R}^{W \times H}$ is used as input to the SLIC algorithm.

$$I = w_r I_r + w_g I_g + w_b I_b \quad (2)$$

where I_r, I_g, I_b are the spectral channels of the HSI with band centers corresponding to the red, green, and blue channels. In our experiments, the weights w_r, w_g, w_b are set to 0.06, 0.63, 0.27 as per values suggested in [15], which are perceptually optimized on human visual data. A panchromatic image captures the variation in the spatial content of the HSI which is not always visible from the image of a single channel. This formulation of I tries to model the RGB version of the HSI.

6 Methods: Two NCM Estimators

Spatial based noise estimators are fast but inaccurate when the data gets mixed. This issue is circumvented by considering spectral based noise estimators at the expense of increased computation cost. Another issue hampering the performance of spatial estimators like in Eq. 1, is the spatial dimensions of the data. For large vectorized images, there is absolutely no correlation between pixels at row/column skips even if they belong to the same material. Our spatial-based estimators handles both cases of accurately estimating noise at low computation cost, as well as being unaffected by spatial dimension. It computes the noise estimates from the 3D cube Y_{orig} , and then vectorizes it to Y , thereby maintaining proper correlations between neighboring pixels in the spatial domain.

6.1 Neighborhood Based (NCM-A)

This noise estimator of Alg. 1 is inspired by earlier spatial based methods, where instead of just looking to the right neighbor, all surrounding eight neighbors of a pixel are accounted for computing the noise level for that pixel. To avoid estimating noise from neighbors of different material, only the ones that share the same superpixel label are considered. The noise is then computed as the difference between the current pixel's value and the weighted sum of values of its neighbors with same superpixel label. Hence the weighting factor is varies according to the layout of the data with ct being total of same label neighbors.

Algorithm 1

NCM-A($I \in \mathbb{R}^{W \times H}$, $Y_{orig} \in \mathbb{R}^{W \times H \times S}$)

```

1:  = SLIC(I)
2:  for each pixel  $(i, j) \in$  do
3:    for each neighbor  $(i', j')$  of pixel  $(i, j)$  do
4:       $ct = 0$ ;  $elem = \Phi$ 
5:      if  $label(i, j) == label(i', j')$  then
6:         $ct = ct + 1$ 
7:         $elem[ct] = Y_{orig}(i', j', :)$ 
8:       $\delta_{orig}(i, j, :) = Y_{orig}(i, j, :) - \frac{1}{ct}(\sum_{k=1}^{ct} elem[k])$ 
9:  Output:  $\delta_{orig} \in \mathbb{R}^{W \times H \times S}$  reshaped into  $\delta \in \mathbb{R}^{N \times S}$ 

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6.2 Cluster Based (NCM-B)

This noise estimator of Alg. 2 is inspired by the classical K-means, where cluster centers are the true representation of the class spectrum, and all data within that class are some deviations away from the center due to noise and other Effects. Once the superpixel labels are assigned, the mean spectrum of each label k is calculated as $\mu(k)$. The noise for each pixel is then computed as the difference between the current pixel's value and the mean spectrum of the same label.

Algorithm 2

NCM-B($I \in \mathbb{R}^{W \times H}$, $Y_{orig} \in \mathbb{R}^{W \times H \times S}$)

```

1:  = SLIC(I)
2:  for each label  $k \in K$  do
3:     $\mu(k)$  = mean of pixels with label  $k$ 
4:    for each pixel  $(i, j) \in$  do
5:       $k = \text{label}(i, j)$ 
6:       $\delta_{orig}(i, j, :) = Y_{orig}(i, j, :) - \mu(k)$ 
7:  Output:  $\delta_{orig} \in \mathbb{R}^{W \times H \times S}$  reshaped into  $\delta \in \mathbb{R}^{N \times S}$ 

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7 Experiments

In this section, we provide simulations to showcase the Effectiveness of our twin algorithms and their comparisons. We analyze results on both synthetic images created from real world spectrum as well as on public dataset, to show the robustness in presence of noise from any unknown distribution.

7.1 Data Description

For the synthetic image shown in Fig. 2, the spectrum contains reflectance values collected from the AVIRIS scene over Moffett Field², CA in 1997 [14]. We chose regions from five classes: Light vegetation, Rock, Dense vegetation, Dry soil and Wet soil. We chose this dataset because it is real-world and noise is included in the spectrum, hence no bias due to prior knowledge of the noise distribution. The data is arranged in stratified layers from each class in chunks of 20×20 pixels, with each spectrum containing 203 channels and 5 classes, resulting in an HSI of size $100 \times 20 \times 203$ of reflectance values.

7.2 Classification Metrics

We chose PCA for dimension reduction followed by K-means clustering to be the classification algorithm. Of course, other complex algorithms for pure pixel classification or end-member extraction can be employed, but those are out of scope for this work. The number of components for PCA was chosen as the number of channels that accounted for 97.5% of the total SNR after MNF transform. Loss is measured as the number of misclassified pixels after MNF denoising.

7.3 Different Variations of Spatial Mixing

We see that the number of misclassified samples in Fig. 6 and Fig. 7 is drastically less compared to the MNF with naive noise approximation in Fig. 3. Even though the number of intermixing of layers increased, both our algorithms were able to accurately approximate the noise, hence leading to better HSI denoising.

²Data available at <http://aviris.jpl.nasa.gov/html/aviris.freedata.html>

In order to further study the Effect of mixing of objects, we shuffled the data blocks around to introduce more class skips along both horizontal and vertical directions, with patterns which occur in real-world datasets like Indian Pines or Salinas. We see that in these cases too, our approach is able to handle the spatial mixing of boundaries accurately. The two class boundary results are shown in Fig. 8, 9 with the stride pattern corresponding to the Salinas dataset. However going by MAF [7] formulation, this is a very bad situation as all class boundary pixels have their noise estimated from their neighbor that belongs to a different class. Similarly, the multiple (four in cases of corner pixels of each class) class boundary results are shown in Fig. 10, 11 respectively, where along each direction, a pixel encounters multiple classes, with the blocky checkerboard pattern corresponding to the Indian Pines dataset. Here also, due to computation of noise in the HSI cube Y_{orig} , results of MNF remain unaffected after vectorization.

7.4 Comparison between the two approaches NCM-A, NCM-B

We compare our two approaches NCM-A (Alg. 1) and NCM-B (Alg.2) in terms of quantitative and timing analysis. Over several experimentations, we found that the NCM-B variant performs better than NCM-A. Because of superpixel averaging, more the number of superpixel averaged, better is the cancellation of noise, under Gaussian noise models, hence better performance of NCM-B (cluster-based method). This is also validated by the misclassified pixels rate of the two algorithms shown in Table 1, and better runtime efficiency.

7.5 Complexity

The cost for computing SLICO superpixel of the panchromatic image is $O(N)$. NCM-A computes the noise for each pixel by looking into its eight adjacent neighbors, hence takes $O(NS)$. NCM-B computes the mean spectra of each superpixel in $O(P)$ time³, the noise computation for all pixels is again $O(N)$, hence the total time is $O((N+P)S)$. For any HSI data $N \gg P$, hence P is relative constant depending on the dataset used. Hence, the time complexity of the both the algorithms is effectively $O(NS)$.

7.6 Experiments on Publicly Available Datasets

We chose the Salinas-A dataset for experimentation. It was collected by the 224-channel AVIRIS sensor over Salinas Valley, CA [14]. It has 86×83 pixels and six classes of radiance spectrum. The 20 water absorption channels were discarded. Fig. 5 shows the generated image for SLIC. The spectrum are added with random Gaussian noise, which are correlated across channels, but independent of signal.

The naive algorithm badly estimates the noise, resulting in bad classification as shown in Fig. 12. The classification results from our twin methods are shown in Fig. 13. Both the algorithms can accurately recover the true spectral features of the data after MNF denoising, illustrated with low error between true and recovered spectrum in Fig. 14.

³ P is the number of pixels grouped in a superpixel.

8 Conclusion

In this work we introduced two spatial based noise estimators for MNF, based on superpixel segmentation of a generated panchromatic image of a HSI. They perform with higher accuracy than the spectral based estimators while having the same computation cost as the spatial based estimators, and with no numerical instability issues. This is relevant in many research areas where the HSI datasets are large, hence a quick and accurate noise estimation method is required to maintain the integrity of MNF denoising.

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Fig. 1.

Raw noisy spectrum of five classes of the Moffett HSI [14]. Light and Dense Vegetation contains spectral signature similarity. Same goes for the Dry and Wet Soil. The parameters of the noise model are unknown.

Fig. 2.
Ground truth image of five materials of synthetic HSI over three levels of spatial rearrangement of pixels to demonstrate the Effect of class mixing.

Fig. 3.

Result of classification of the sample HSI after MNF denoising. K-Means is used for assigning labels. As classes keep on mixing, noise is computed between pixels belonging to different classes as per MAF. Poor NCM estimates occur due to bad estimation of noise, hence performance of MNF degrades.

Fig. 4. Result of classification of the HSI after OMNF denoising. With further mixing the results degrade due to instability on solving the regressions.

Fig. 5.
Left to Right: Original images corresponding to red (665.59 nm), green (589.31 nm), and blue (491.90 nm) wavelengths and Simulated Panchromatic image for the Salinas-A dataset.

Fig. 6. Result of classification of the sample HSI after MNF denoising with NCM-A Alg. 1. Across levels of mixing, the classification accuracy of a pixel does not degrade much due to proper estimation of noise from neighbors of same class.

Fig. 7. Result of classification of the sample HSI after MNF denoising with NCM-B Alg. 2. Across levels, the classification accuracy of a pixel does not degrade much due to proper estimation of noise from the mean spectrum of its superpixel.

Fig. 8. Classification of the sample HSI after MNF denoising with NCM-A. Note that even when there are large class skips from interboundary pixels, NCM-A obtains proper noise estimates

Fig. 9. Classification of the sample HSI after MNF denoising with NCM-B. Here too, NCM-B yields proper noise estimates.

Fig. 10. Classification of the sample HSI after MNF denoising with NCM-A. For this pattern, we get two neighboring classes for boundary pixels, with four for the corner ones. Weighting of neighbors with same labels gives better noise estimate.

Fig. 11.
Classification of the sample HSI after MNF denoising with NCM-B.

Fig. 12.

Salinas-A HSI. Left: Ground Truth of 7 classes. Right: Classification after MNF on the noisy cube, with added artificial band-correlated Gaussian noise. It is evident that the naive noise estimation by considering one spatial neighbor, results in poor denoising of the spectrum, hence bad classification accuracy.

Fig. 13.

Salinas-A HSI. Classification after noise estimation using Left: NCM-A (Alg. 1), which takes 0.173s. Right: NCM-B (Alg. 2) which takes 0.099s. The results are significantly improved compared to the naive approach. We also see that NCM-B performs better than NCM-A, specially near the pink, black and yellow patches at the bottom right, and in terms of computation time too.

Fig. 14.

Salinas-A HSI. Top: True spectra from six classes are shown with solid lines. Noise correlated across bands are shown in dashes. Bottom: Difference between the true and estimated spectra. Low value of reflectance errors (< 10) compared to the strength of signals (> 1000) demonstrate that NCM-B accurately estimates the noise introduced in this HSI.

Table 1

Comparison of approaches: NCM-A (Alg. 1) and NCM-B (Alg.2). Columns 3,4,5 shows the number of misclassified pixels in each case. We can see that given same patterns, NCM-B performs better than NCM in terms of erroneous pixels. NCM-B also has a speedup factor of 2 over NCM-A. Simulations carried out on a PC with Intel i7 – 7700@3:6GHz CPU, 32GB Ram.

Scenario	Execution Time	# Pixels (left)	# Pixels (middle)	# Pixels (right)
Fig. 6 NCM-A	~ 0.024s	7	8	8
Fig. 7 NCM-B	~ 0.011s	4	4	4
Fig. 8 NCM-A	~ 0.024s	6	5	5
Fig. 9 NCM-B	~ 0.011s	5	5	5
Fig. 10 NCM-A	~ 0.024s	7	8	8
Fig. 11 NCM-B	~ 0.011s	4	4	4