Hyperspectral Image Denoising Using Low Pass Sparse Banded Filter Matrix for Improved Sparsity based Classification

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Abstract

The recent advance in sensor technology is a boon for hyperspectral remote sensing. Though Hyperspectral images (HSI) are captured using these advanced sensors, they are highly prone to issues like noise, high dimensionality of data and spectral mixing. Among these, noise is the major challenge that affects the quality of the captured image. In order to overcome this issue, hyperspectral images are subjected to spatial preprocessing (denoising) prior to image analysis (Classification). In this paper, authors discuss a sparsity based denoising strategy which uses low pass sparse banded filter matrices (AB filter) to effectively denoise each band of HSI. Both subjective and objective evaluations are conducted to prove the efficiency of the proposed method. Subjective evaluations involve visual interpretation while objective evaluations deal with the computation of quality matrices such as Peak Signal to Noise Ratio (PSNR) and Structural Similarity (SSIM) index at different noise variance. In addition to these, the denoised image is followed by a sparsity based classification using Orthogonal Matching Pursuit (OMP) to evaluate the effect of various denoising techniques on classification. Classification indices obtained without and with applying preprocessing are compared to highlight the potential of the proposed method. The experiment is performed on standard Indian Pines Dataset. By using 10% of training set, a significant improvement in overall accuracy (84.21%) is obtained by the proposed method, compared to the other existing techniques.

Keywords: Classification, Hyperspectral image denoising, Low pass sparse banded filter matrix (AB filter), Orthogonal Matching Pursuit

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1. Introduction

Hyperspectral remote sensing involves capturing of images of objects on the earth surface at various contiguous spectral bands. These images with high spectral and spatial information are arranged layer by layer to form a hyperspectral data cube. Despite of the abundant information available in each band of Hyperspectral image (HSI), they are subjected to various challenges such as noise, huge size of data and spectral mixing. Several researches have been progressing to find optimum solutions for these issues.

The quality of the image captured is greatly influenced by the presence of noise induced in the HSI. Therefore, to improve the image quality prior to data analysis, denoising is performed as a spatial preprocessing technique. Wei He et al. proposed an adaptive iterative noise adjustment technique that uses low rank matrix approximation for effective denoising of HSI. Sparse analysis regularization is employed for HSI denoising which uses 3D over-complete wavelet dictionary. In order to effectively denoise a large class of signals, Selesnick et.al. proposed a method which combines LTI filtering and sparsity based denoising. Some of the other existing denoising technique includes denoising by total variation, Principal Component Analysis and Wavelet shrinkage, Singular value decomposition etc.

The pre-processed data is used for various data analysis like classification, target detection etc. One of the commonly used classifier namely Support Vector Machine (SVM) is used by J A Gualtieri et.al. for solving regression and supervised classification problems of AVIRIS hyperspectral dataset. A novel method for HSI classification is introduced by Chen et al. which sparsely represents the hyperspectral test pixel as a linear combination of a few number of training samples from a well organized dictionary matrix. Some of the other classification techniques include kernel based classifications and probability based approaches.

In this paper, we discuss a spatial preprocessing technique for HSI denoising which uses low-pass sparse banded filter matrices (AB filter) to effectively denoise each band of HSI prior to sparsity based classification using Orthogonal Matching Pursuit (OMP). This designed filter is applied both column-wise and row-wise on the noisy band for denoising the image. The experiment uses standard Indian Pines dataset corrupted with Gaussian noise at different variance. The effectiveness of the proposed method (denoising using low pass sparse banded filter matrices) is evaluated by comparing its qualitative and quantitative results obtained with other existing preprocessing techniques. Comparison is done based on visual interpretations and calculation of PSNR and SSIM values. The preprocessing is followed by sparsity based OMP classification, whose classification indices are assessed to prove the potential of the proposed method.

Rest of the paper is as follows. Section 2 describes the HSI denoising using low-pass sparse banded filter matrices. An overview of sparsity based OMP classification is given in section 3. Proposed method is presented in Section 4. Experimental results and analysis are discussed in Section 5 and section 6 concludes the paper.

2. HSI Denoising Using Low Pass Sparse Banded Filter Matrices (AB filter)

Hyperspectral dataset is a 3-D datacube represented as \( X \in \mathbb{R}^{n \times n \times n} \) where \( n_x \times n_y \) represents total number of pixels and \( n_z \) represents the number of bands. Noise induced in this data is eliminated to a large extent by introducing various preprocessing (denoising) techniques. It is expected that, after preprocessing, the denoised image preserves the edge information in the original noisy image. This paper uses an efficient denoising strategy using low pass sparse banded filter matrix (AB filter) to remove the unwanted information in the HSI.

2.1. Banded Filter Matrices

The authors in their paper has introduced the design of non causal zero phase recursive high pass filters (HPF) and low pass filters (LPF) in terms of banded filter matrices. The difference equation of first order Butterworth HPF in matrix form is given as,

\[
At = Bs
\]

where \( A \) and \( B \) are the banded filter matrices of size \((N-1) \times (N-1)\) and \((N-1) \times N\) respectively, \( t \) is the filter output and \( s \) is the input signal. \( N \) is the length of the input signal. The filter output \( t \) is given by,
where \( t \) is of size \(((N-1) \times 1)\).

The transfer function of the non-causal zero-phase higher order \((n)\) high-pass Butterworth filter is\(^3\),

\[
\frac{B(z)}{A(z)} = H(z) = \frac{(-z + 2 - z^{-1})^n}{(-z + 2 - z^{-1})^n + \alpha(z + 2 + z^{-1})^n}
\]

Or,

\[
H(z) = 1 - \frac{\alpha(-z + 2 - z^{-1})^n}{(-z + 2 - z^{-1})^n + \alpha(z + 2 + z^{-1})^n}
\]

The frequency response of this filter is unity gain at \( \omega = \pi \) and the frequency response is maximally flat at \( \omega = 0 \). Hence it is called a zero-phase digital filter. Order of the filter \((n)\) and parameter \( \alpha \) defines the filter. \( \alpha \) is given as,

\[
\alpha = \left( \frac{1 - \cos \omega_c}{1 + \cos \omega_c} \right)^n
\]

where \( \omega_c \) is the cut off frequency. The transfer function of LPF is derived from HPF. This is given by,

\[
L(z) = 1 - H(z)
\]

The zero-phase low-pass Butterworth filter given as\(^3\),

\[
L(z) = \frac{\alpha(-z + 2 - z^{-1})^n}{(-z + 2 - z^{-1})^n + \alpha(z + 2 + z^{-1})^n}
\]

with a 2n-order zero at \( z = -1 \). The LPF equation is given by,

\[
t = Is - A^{-1}Bs
\]

where \( Is \) is identity matrix, \( A \) and \( B \) are banded sparse matrices of dimension \((N-2n) \times (N-2n)\) and \((N-2n) \times N\) respectively. Matrix \( A \) is a symmetric matrix. Both \( A \) and \( B \) have \( n \) diagonals above and below the main diagonal.

2.2. Image Denoising using Sparse Banded Filter Matrices

In the proposed method, in order to remove the noise present in each band, the designed sparse banded LPF is applied both row wise and column wise. The proposed method is as follows:

1. Let the input HSI image be \( s \in R^{M \times N} \), with row represented as \( s_{row} \in R^{N} \) and column as \( s_{col} \in R^{M} \).
2. The input image is subjected to border repetition. This is represented by \( S \in R^{(M+2n) \times (N+2n)} \), where \( n \) is the order of the filter. The dimension of sparse banded matrices \( A \) and \( B \) is \((N \times N) \times (N \times (N + 2n))\) respectively. Matrix \( A \) is a symmetric matrix. Both \( A \) and \( B \) have \( n \) diagonals above and below the main diagonal.
3. Each row of the new image is represented as \( s_{row} \in R^{(N+2n)} \) which is given as an input to the LPF equation \( t = Is - A^{-1}Bs \) to obtain the filter output, \( t_{row} \in R^{N} \).
4. Step 3 is repeated for all the rows in the input image. This is represented as, \( T_{row} \in R^{M \times N} \).
5. The same is repeated for all columns of the image. This is given as \( s_{col} \in R^{(M+2n)} \).
6. The mathematically expression for filter output sequence for each column is given as,

\[
t_{col} = s_{col} - A^{-1}BS_{col}
\]

where \( t_{col} \in R^{N} \).
7. The whole columns operated in the image is given as \( T_{col} \in R^{M \times N} \).
8. The output image (denoised image) is obtained by,
3. OMP Based HSI Classification

In a sparsity based classification, the test pixel vector is sparsely represented using a few numbers of training samples which are selected randomly from the entire hyperspectral data. Orthogonal Matching Pursuit (OMP) is one of such sparsity based greedy algorithms used for hyperspectral image classification\(^\text{7}\). Let us consider the HSI data to be \(D\)-dimensional. The randomly selected training samples are concatenated to form the dictionary matrix which is represented as \(A = [A_1, A_2, \ldots, A_L]\). The subdirectory of dictionary matrix \(A\) is represented as \(A_i = [a_{i1}, a_{i2}, \ldots, a_{in}]\). \(A_i\) is the training vector belonging to \(i^{th}\) class where \(i \in L\) and \(L\) is the total number of classes. The constrained sparse optimization problem is given by,

\[
\hat{s} = \arg \min_s \|s\|_0 \quad \text{subjected to} \quad As = t
\]

where \(s\) is the sparse vector used to find the class labels of the test pixel vectors. Class of each test pixel vector is determined by,

\[
\text{Class}(t) = \arg \min_{i=1 \ldots L} (r_i)
\]

Detailed description about Orthogonal Matching Pursuit is given in\(^\text{7}\).

4. Proposed Method

The present experiment involves denoising of HSI using low pass sparse banded filter matrices (AB filter) which is further followed by sparsity based OMP classification. The experiment is conducted on standard Indian Pines dataset. The two major steps in the proposed method are spatial preprocessing and classification. The flow graph of the proposed method is given in Fig. 1.

Fig. 1. Flow graph of the proposed method.

**Spatial Preprocessing:** Noise is one of the major challenges faced in HSI data analysis which cause reduction in the classification accuracy. This issue is resolved to a large extent by the usage of a spatial preprocessing technique called denoising. Denoising of HSI using low pass sparse banded filter matrices (AB filtering) helps to effectively denoise HSI without losing the edge information.

**Classification:** During classification, the entire HSI data is separated into training and testing samples. In the training phase, the pixels are randomly selected from the HSI data to form the dictionary matrix. The whole samples or samples other than the training samples are given as test set for classification. Among the various classification approaches, the sparsity based approaches are fast and use only a few number of training samples to represent the test pixel vector. In this experiment, sparsity based Orthogonal Matching Pursuit (OMP) algorithm is used for the classification of HSI.

5. Experimental Results Analysis

This section includes a brief description of dataset used for the experiment, accuracy assessment measures and analysis of the effect of various preprocessing techniques on sparsity based hyperspectral image classification.
5.1. Dataset Description

The experiment uses standard Indian Pines dataset for HS data analysis. It consists of 224 contiguous spectral bands, each with 145x145 pixels. The bands without any useful information and water absorption bands are removed prior to data processing. The images are captured using AVIRIS sensor over a range of 0.4 to 2.5m with spatial resolution of 20m per pixel and spectral resolution of 10nm. Agriculture, lane highways, forest, rail line, roads, housing and some built structures are parts of the dataset.

5.2. Accuracy Assessment Measures

Accuracy assessments are conducted both qualitatively (subjective) and quantitatively (objective). Subjective assessment involves visual interpretation of denoised images obtained by applying various preprocessing techniques such as TV denoising, Wavelet based denoising and AB filter denoising. Quantitative assessment is done by computing the quality matrices such as Peak signal to Noise Ratio (PSNR) and Structural Similarity (SSIM) index. Another objective assessment is computing the confusion (error) matrix from which various classification indices like overall, class wise and average accuracies are found. Kappa coefficient is also calculated to evaluate the performance of various classifiers.

5.3. Results and Discussion

In this section, the effectiveness of low pass sparse banded filter matrices (proposed method) for HSI denoising is exhibited by comparing the same with other existing preprocessing methods like denoising by Total Variation (Euler Lagrange ROF) and wavelet based denoising. The evidence for this is provided by visual interpretation of denoised images, calculation of PSNR and SSIM and by the analysis of the effect of various existing preprocessing methods (Total Variation (TV) denoising and Wavelet based denoising) on classification accuracy.

1. **Subjective evaluation of preprocessing:** This experiment uses Band 11 of Indian pines dataset as a sample band which is corrupted by noise at different variances (0.00005, 0.0001, 0.0005, 0.001, 0.005, 0.01 and 0.05). Fig. 2(a) represents the Band 11 of Indian pines dataset added with additive Gaussian noise with variance $\sigma = 0.00005$. The effect of Total variation denoising and wavelet based denoising are given in Fig. 2(b) and Fig. 2(c) respectively. Denoising using low pass sparse banded filter matrices (AB filter) is given in Fig. 2(d). By subjective evaluation, it is perceived that the proposed method gives visually good results compared to other mentioned methods. The designed LPF is applied both row-wise and column-wise for denoising each band of hyperspectral image. This method helps in smoothing the image while preserving the edge information.

2. **Objective evaluation of preprocessing:** Table 1 and Table 2 give quantitative explanation for the above description by computing the quality metrics such as Peak Signal to Noise Ratio (PSNR) and Structural Similarity (SSIM) Index respectively. In the PSNR calculation, a standard reference image is compared with the noisy image and denoised image. An increase in the PSNR value of denoised image (compared to noisy) represents that it preserves the information in the original image while denoising the same. As the noise variance increases, the signal to noise ratio decreases and thereby decreases the PSNR value. Graphical representation of Table 1 is given in Fig. 3. SSIM measures the structural similarity of two given images. In this experiment, it is used to know the similarity between noisy or denoised image compared to the original reference image. A unity value for SSIM reveals that the two images are structurally equivalent. i.e., as the SSIM value is close to unity, it shows better similarity between images. An increase in the noise variance causes the SSIM value to decrease. Graphical representation of Table 2 is given in Fig. 4. In this paper, PSNR and SSIM values at different noise levels (variance) are calculated to analyse the effect of various preprocessing techniques on hyperspectral image. Table 1 and Table 2 show that the proposed technique outperforms the TV denoising in both the quality metric analysis. Wavelet based denoising shows a slight improvement in quality metrics compared to the proposed method since it undergoes high diffusion.
3. **Analysis of classification**: The effect of various preprocessing techniques in improving the classification accuracy of hyperspectral image classification is also discussed in this section. The proposed method uses sparsity based HSI classification using Orthogonal Matching Pursuit (OMP). In this, the test pixel vector is sparsely represented by a few numbers of training samples which are selected randomly from the entire samples. From the total samples, a few samples (10%, 20%, 30% and 40%) are given for training and rest are given for testing. Table 3 shows the significance of using preprocessing techniques prior to sparsity based hyperspectral image classification, by comparing the classification indices obtained with and without applying preprocessing. Analysis of Table 3 shows that, the classification using proposed method (AB filter denoising) outperforms the existing denoising methods such as Total Variation denoising and Wavelet based denoising. Though quality metric analysis of wavelet denoising has given a better result compared to AB filter denoising, it fails to provide good classification results as it does not preserve much of the edge information of the original noisy image (due to high diffusion). It is also perceived that, there is an increase in the classification accuracy with increase in the number of training samples taken for classification. With only 10% of samples, the proposed method provides a significant improvement in overall accuracy, i.e. 84.21% while other techniques like TV denoising and Wavelet based denoising gives 78.30% and 81.36% respectively. Our method gives an overall accuracy of 94.04% by taking 40% training samples. Fig. 5(a) shows the test set (ground truth). Fig. 5(b) gives the classification map of Indian Pines dataset without applying any denoising techniques. Fig. 5(c) and Fig. 5(d) are the classification maps obtained after applying TV denoising and wavelet based denoising respectively. The performance of the proposed techniques with different training samples (10%, 20%, 30% and 40%) is given in Fig. 5(e) - Fig. 5(h) respectively.

![Original image](image1)
![TV Denoising](image2)
![Wavelet Denoising](image3)
![AB filter Denoising](image4)

Fig. 2. Preprocessing on Indian Pines dataset (Band 11 with Gaussian noise (σ=0.00005)) using different denoising methods.

<table>
<thead>
<tr>
<th>Gaussian Noise Variance</th>
<th>PSNR value (in dB)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Noisy</td>
<td>Denoised</td>
</tr>
<tr>
<td></td>
<td>TV-ROF denoising</td>
<td>Wavelet denoising</td>
</tr>
<tr>
<td>0.05</td>
<td>15.7256</td>
<td>21.4049</td>
</tr>
<tr>
<td>0.01</td>
<td>21.9131</td>
<td>26.4788</td>
</tr>
<tr>
<td>0.005</td>
<td>24.3433</td>
<td>28.3427</td>
</tr>
<tr>
<td>0.001</td>
<td>30.2343</td>
<td>32.7163</td>
</tr>
<tr>
<td>0.0005</td>
<td>33.9723</td>
<td>34.9635</td>
</tr>
<tr>
<td>0.0001</td>
<td>39.9723</td>
<td>40.9901</td>
</tr>
<tr>
<td>0.00005</td>
<td>42.9958</td>
<td>43.5645</td>
</tr>
</tbody>
</table>

Fig. 3. Graphical representation of PSNR value of Noisy and denoised image using AB filter
Table 2. Quantitative analysis of SSIM calculation

<table>
<thead>
<tr>
<th>Gaussian Noise Variance</th>
<th>SSIM value</th>
<th>Noisy</th>
<th>Denoised</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>TV-ROF</td>
<td>Wavelet denoising</td>
<td>AB filter denoising</td>
</tr>
<tr>
<td>0.05</td>
<td>0.0366</td>
<td>0.1702</td>
<td>0.8045</td>
</tr>
<tr>
<td>0.01</td>
<td>0.1366</td>
<td>0.3317</td>
<td>0.9546</td>
</tr>
<tr>
<td>0.005</td>
<td>0.2177</td>
<td>0.4195</td>
<td>0.9705</td>
</tr>
<tr>
<td>0.001</td>
<td>0.5052</td>
<td>0.6523</td>
<td>0.9762</td>
</tr>
<tr>
<td>0.0005</td>
<td>0.6685</td>
<td>0.7602</td>
<td>0.9771</td>
</tr>
<tr>
<td>0.0001</td>
<td>0.9085</td>
<td>0.9225</td>
<td>0.9805</td>
</tr>
<tr>
<td>0.00005</td>
<td>0.9519</td>
<td>0.9565</td>
<td>0.9858</td>
</tr>
</tbody>
</table>

Fig. 4. Graphical representation of SSIM value of Noisy and denoised image using AB filter

(a) Ground truth (b) OA=76.65% (c) OA=78.30% (d) OA=81.36%

(e) OA=84.21% (f) OA=89.63% (g) OA=91.79% (h) OA=94.04%

Fig. 5. Indian Pines Dataset: (a) Ground truth. Classification maps of MC 5: (b) Without Preprocessing, (c) With TV denoising, (d) With Wavelet Denoising, (e)-(h) With AB filtering (10%, 20%, 30% and 40% respectively)

6. Conclusion

This paper discusses about an efficient denoising technique using low pass sparse banded filter matrix (AB filter) for denoising each band of hyperspectral image prior to sparsity based classification using Orthogonal Matching Pursuit (OMP). The denoising is performed by applying the designed low pass filter matrix both row-wise and column-wise on the noisy image. The experiment is conducted on standard Indian Pines dataset. Experimental analysis concludes that the proposed method outperforms the existing methods in both subjective and objective evaluations.

References


### Table 3. OMP based classification results obtained without and with preprocessing on Indian Pines dataset

<table>
<thead>
<tr>
<th>Class</th>
<th>Without Preprocessing</th>
<th>TV denoising</th>
<th>Wavelet based denoising</th>
<th>AB filter denoising</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percentage of training</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td>Alfalfa</td>
<td>93.48</td>
<td>93.48</td>
<td>93.48</td>
<td>100.00</td>
</tr>
<tr>
<td>Corn-notill</td>
<td>61.48</td>
<td>69.26</td>
<td>77.24</td>
<td>77.17</td>
</tr>
<tr>
<td>Corn-mintill</td>
<td>66.99</td>
<td>64.94</td>
<td>68.07</td>
<td>74.34</td>
</tr>
<tr>
<td>Corn</td>
<td>59.07</td>
<td>66.67</td>
<td>64.56</td>
<td>62.45</td>
</tr>
<tr>
<td>Grass-pasture</td>
<td>91.51</td>
<td>91.72</td>
<td>83.85</td>
<td>95.24</td>
</tr>
<tr>
<td>Grass-trees</td>
<td>94.79</td>
<td>97.26</td>
<td>96.85</td>
<td>98.77</td>
</tr>
<tr>
<td>Grass-pasture-mowed</td>
<td>92.86</td>
<td>96.43</td>
<td>100.00</td>
<td>96.43</td>
</tr>
<tr>
<td>Hay-windrowed</td>
<td>97.70</td>
<td>96.86</td>
<td>96.44</td>
<td>97.49</td>
</tr>
<tr>
<td>Oats</td>
<td>100.00</td>
<td>100.00</td>
<td>100.00</td>
<td>100.00</td>
</tr>
<tr>
<td>Soybean-notill</td>
<td>73.97</td>
<td>71.81</td>
<td>77.98</td>
<td>84.16</td>
</tr>
<tr>
<td>Soybean-mintill</td>
<td>76.33</td>
<td>77.43</td>
<td>79.80</td>
<td>84.03</td>
</tr>
<tr>
<td>Soybean-clean</td>
<td>56.32</td>
<td>59.19</td>
<td>59.87</td>
<td>62.56</td>
</tr>
<tr>
<td>Wheat</td>
<td>98.54</td>
<td>98.54</td>
<td>98.05</td>
<td>98.05</td>
</tr>
<tr>
<td>Woods</td>
<td>90.91</td>
<td>92.96</td>
<td>95.57</td>
<td>95.57</td>
</tr>
<tr>
<td>Buildings-Grass-Trees-Drives</td>
<td>57.51</td>
<td>56.22</td>
<td>72.54</td>
<td>70.21</td>
</tr>
<tr>
<td>Stone-Steel-Towers</td>
<td>97.85</td>
<td>94.62</td>
<td>98.92</td>
<td>97.85</td>
</tr>
</tbody>
</table>

| Overall Accuracy   | 76.65 | 78.30 | 81.36 | 84.21 | 89.63 | 91.79 | 94.04 |
| Average Accuracy   | 81.83 | 82.96 | 85.20 | 87.14 | 91.79 | 92.82 | 94.75 |
| Kappa              | 0.7341 | 0.7527 | 0.9001 | 0.8200 | 0.8817 | 0.9064 | 0.9320 |