

Noise Removal in Hyperspectral Images using Spectral Spatial Adaptive Sparse Representation

Soumya C S¹, Dr Thippeswamy G²P.G. Student, Department of Computer Science and Engineering, BMSIT&M, Bangalore, Karnataka, India¹Professor and HoD, Department of Computer Science and Engineering, BMSIT&M, Bangalore, Karnataka, India²

ABSTRACT: Hyperspectral images (HSI) are generally the satellite images. These images often have a problem of noise due to which the image is degraded. These degraded images if used in a right way by eliminating the noise, can be very effective in many fields such as defense, health care, agriculture, pollution monitoring and so on. So, there is always a scope for the noise removal in HSI. This project aims at providing a noise free estimation of the HSI using the novel Spectral Spatial Adaptive Sparse Representation (SSASR) technique. There are three steps that are followed in removing the noise from the HSI using the SSASR technique. First, the HSI is divided into a number of non-overlapping spectral bands. These bands contain highly similar spectral characteristics. Second, the spatially similar local points are obtained in the spatial domain for every single spectral band. By doing the above two steps, the spectral and the spatial similar pixels can be formed as a group. Next and the final step, the highly correlated and similar pixels from the above formed group is used in order to provide a denoised image using the sparse coding technique. The proposed SSASR method is evaluated by different objective metrics in simulated experiments.

KEYWORDS: Hyperspectral image (HSI) denoising, sparse representation (SR), spatial similarity, spectral correlation.

I. INTRODUCTION

Hyperspectral Images fall under the category of the spectral images, which gathers and processes the data throughout the electromagnetic spectrum. This means that the entire electromagnetic spectrum is divided into a number of spectral bands. A human being can recognize only three bands Red, Blue, Green whereas the HSI's are divided into many more continuous and distinct bands of the spectral cube. Hence, HSI's are seen even outside the visible range. The main aim of the HSI is to obtain the spectrum for every single pixel in the image in order to find the objects, identify the materials and detecting the processes. Noise in general refers to anything that is unwanted. In image processing also, noise refers to something that deteriorates the quality of the image. There are different types of noise in the image such as Gaussian noise, impulse noise, shot noise, quantization noise and so on. In this project, we try to focus mainly on the Gaussian noise. Gaussian noise is mainly caused when there is poor illumination or very high temperature. In the Spatial band of acquiring the HSI's, the entire spectrum or the hyper cube is divided into a set of bands. First, the hyper cube is converted to a 2-D block and from this 2-D block the bands are split and these different bands will have a different noise at different pixel level. Hence the 'x' and the y coordinates are considered. The 'z' coordinates are not considered into account. In a spectral band of acquiring the HSI's, the whole spectrum is treated as a 2-D block with single colored pixels. Hence this covers the 'x' and the 'z' coordinates, leaving behind the 'y' axis. The same concept is used in the project to find the local similar pixels. A natural signal is said to be sparse signal if that can be expressed efficiently as a linear combination of a few small number of basis vectors. As HSI's unfortunately suffer from the annoying degradations due to the noise present, there is a need for eliminating the noise which will hinder the visual aspect of the image. This also affects the processing of the image classification, unmixing and the target detection. Hence, considering both the spectral and the spatial, we eliminate the noise to the maximum extent.

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II. RELATED WORK

The projection site is used for maintaining and reducing the aspects of hyperspectral images based on Locality-preserving projection as well as local Fisher discriminant analysis. These techniques are considered slow after the hyperspectral data are considered after classification of Gaussian mixing in a dimensional subspace to form a local geometric structure. Local spatial information should be used to be more strictly multimodal spectral features [1]. A new supervised segmentation algorithm for remotely sensed hyperspectral image data which integrates the spectral and spatial information in a Bayesian framework is introduced in this paper. To learn the posterior probability distributions from the spectral information, a multinomial logistic regression (MLR) algorithm is first used with the help of a subspace projection method to better characterize noise and highly mixed pixels. Then, using a multilevel logistic Markov-Gibbs Markov random field prior, contextual information is included. Finally, by the min-cut-based integer optimization algorithm, a maximum a posteriori segmentation is efficiently computed. The proposed segmentation approach is experimentally evaluated using both simulated and real hyperspectral data sets, exhibiting state-of-the-art performance when compared with recently introduced hyperspectral image classification methods. The integration of subspace projection methods with the MLR algorithm, combined with the use of spatial-contextual information, represents an innovative contribution in the literature. This approach is shown to provide accurate characterization of hyperspectral imagery in both the spectral and the spatial domain [2]. In hyperspectral remote sensing image classification, multiple features, e.g., spectral, texture, and shape features, are employed to represent pixels from different perspectives. To properly collect most of the features that have been promised to always do a good classification performance. In this article, we consistently integrate many features together and submit the alignment frame definition to achieve a low-dimensional unified representation of the many features of the subsequent categorization. The purpose of each feature is its unique contribution to the unified representation of the work to simultaneously optimize the weight. This plan considers many characteristics of less physical representation of a significant size, characterized by specific statistical characteristics. Experiment on the use of hyperspectral and hyperspectral data sets of spectral optical system imaging spectrometer under the use of digital image collection categorization indicates that this plan is effective [3]. Hyperspectral data appears to be increasingly important in recent years. However, handling large scale data sizes as a hyperspectral data application is a challenge to the user community who still are amateur. Efficient compression techniques are essential, and compression damage, in particular, has a role to play, providing results of Remote Sensing App remains frivolous. To take data quality reviews, appropriate user-applications require proper remedies for distortion. Quality criteria are designed to define their needs and specifications and are major interest in developing new sensors. This paper proposes a method of evaluating quality standards in relation to hyperspectral images. The goal is to provide quality related criteria to the effect of many classification applications impairments. Different quality criteria are considered. Some are traditionally used in image and video coding and are adapted here to hyperspectral images. Others are specific to hyperspectral data. Degradation quality hyperspectral AVIRIS We offer two advanced criteria adaptation in the presence of a variety of images. Finally, the five criteria are chosen to give an accurate representation of the degradation level affecting nature and hyperspectral data [4]. In this paper, a novel method to characterize random noise sources in hyperspectral (HS) images is proposed. Noise is described using a parametric model that accounts for the dependence of noise variance on the useful signal. Such model takes into account the photon noise contribution and is therefore suitable for noise characterization in the data acquired by new-generation HS sensors where electronic noise is not dominant. A new algorithm is developed for the estimation of noise parameters which consists of two steps. First, the noise and signal realizations are extracted from the original image by resorting to the multiple-linear-regression-based approach. Then, the model parameters are estimated by using a maximum likelihood approach. The new method does not require the intervention of a human operator and the selection of homogeneous regions in the scene. The performance of the new technique is analyzed on simulated HS data. Results on real data are also presented and discussed. Images acquired with a new-generation HS camera are analyzed to give an experimental evidence of the dependence of random noise on the signal level and to show the results of the estimation algorithm. The algorithm is also applied to a well-known Airborne Visible/Infrared Imaging Spectrometer data set in order to show its effectiveness when noise is dominated by the signal-independent term [5].

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III. SSASR METHOD FOR DENOISING HSI

Let $Z \in \mathbb{R}^{M \times N \times B}$ represent one HSI, where $M \times N$ is the size of each spectral band, and B is the number of spectral bands. The commonly used image degradation model for each spectral band Z_i ($i \in [1, B]$) can be denoted by

$$Z_i = X_i + N_i$$

where X_i and N_i represent the clean and noisy components, respectively.

As shown in Fig. 1, the proposed SSASR method consists of three main phases: spectral-adaptive band-subset partition, spatial-adaptive local related pixel searching, and SR-based noise-free estimation. First, according to the Pearson-correlation-coefficient-based metric, a coarse-to-fine band-subset partition is presented to separate the HSI into various band subsets. Each band subset contains uninterrupted spectral bands with high spectral correlation, whereas the correlation among spectral bands in altered band subsets is low. Second, by smearing the shape-adaptive (SA) local region searching on the weighted average generated fused image, local identical region can be determined for each central spectral pixel. Each similar region consists of multiple highly similar spectral pixels. Finally, by solving an SR-based optimization problem, the noise-free approximation for each group of spectral pixels with high spectral correlation and spatial similarity can be generated. Specifically, all the spectral pixels belonging to each group are vectorized to form a sparse matrix, which are jointly sparsely coded and reconstructed to generate the noise free image.

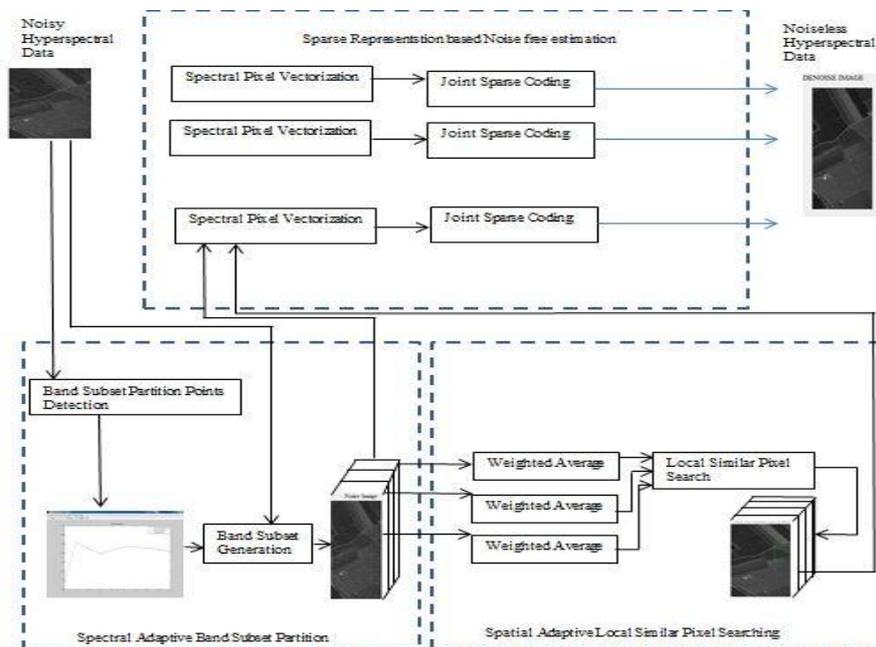


Fig 1 : Architecture of SSASR

A. Spectral-Adaptive Band-Subset Partition

The Hyperspectral images are a collection of a number of bands unlike that of the normal image which can be seen through with our eye as Red, Blue and Green. We need to know the advantage of having these different bands in this project. In this project, 11 bands for the image has been considered. First, we need to find the similarity between the 2 adjacent/consecutive bands namely I_i and I_j . The correlation curve C needs to be generated for these adjacent spectral bands. It can be seen from the system architecture Fig 1, that the Correlation Coefficient Curve is seen in the Red Color.

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There might be some sharp drops and few stable points. Therefore, by detecting these sharp drops in curve C the band subset partition can be achieved. The Coarse-to-Fine band subset partition can be achieved in 2 steps.

- Coarse Band Subset Partition

From the Correlation coefficient Curve C, Local valley points are detected. At any point 'i' in the graph, if C(i) meets the condition below, then the local valley is that point which can be regarded as one initial partition point.

$$\begin{aligned}C(i+1) - C(i) &> 0 \\ C(i) - C(i-1) &< 0\end{aligned}$$

- Fine Band Subset Partition

In order to represent the characteristics of each spectral band, an average weighted fused image is generated that would in turn have the weighted average on all the spectral bands. Hence, with the introduction of the weights, the spectral band image degradations will have a significant impact on the fused image.

B. Spatial-Adaptive Local Similar Pixel Searching

In the Hyperspectral images, a neighborhood always has a large number of pixels related to the same material. Based on this concept, similar pixels are searched in the spatial region and together with these similar pixels, a noise free estimation can be done. Then, each local region, which contains the spatially similar pixels is determined for central pixel. In this project, we try to get the local similar pixels in the above mentioned way for every band subset. The similar pixels are identified in every band and each such similar pixel is given a border of green color to show the difference.

C. SR-Based Noise-Free Estimation

Based on the spectral and the spatial details acquired in the previous steps, each pixel in the spectral band subset will correspond to the local SA region. Hence, by ordering all the pixels in each column by column, a matrix can be obtained. Since all the spectral pixels in the matrix are highly similar, they should share a common sparsity pattern with different sets of coefficients, which can be modeled as a joint sparse coding. In this SR based Noisefree estimation there are three steps that are followed. First, is the iterative regularization followed by updating the noise-free estimated in the matrix. Finally, the noise-free estimation of the pixels is updated. Let us briefly discuss what are these three steps in detail.

- Iterative Regularization

This iterative regularization can be achieved by adding the filtered noise back to the denoised image which means that from the spectral and the spatial details which we have acquired, we have the pixels which are noise-free and these pixels can be used to represent the denoised image. By considering that each spectral band is also one 2-D image, the iterative regularization can be introduced to the HSI in a band-by band manner.

- Matrix Noisefree estimation Update

Each Matrix obtained will be considered as a whole and the noise-free estimation is done in the entire matrix. By vectorizing all the pixels in the spectral band, then we can consider the entire matrix at once which can be noise-free matrix.

- Pixel Noisefree estimation Update

Once the entire matrix has the noise-free estimation, we need to do it on the pixel level. For every pixel, a noise-free estimation is done and further in turn the noisy pixel is updated with the denoised pixel to form denoised image. By Following the above the three mentioned steps iteratively, we can get a denoised image.

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III. EXPERIMENTAL RESULTS

A hyperspectral image data set is considered with 11 bands with a Gaussian noise in the range of $\sigma \in \{[0, 0.1], [0, 0.2]\}$. First, the hyperspectral image is loaded with the Gaussian noise in the range $\sigma \in \{[0, 0.1], [0, 0.2]\}$ in the MATLAB simulator. Then the band subset partition points are detected in 2 steps. First will be the coarse band partition and followed by the fine band partition. Then a weighted based image is generated by performing the weighted average on all the spectral bands. After the weights are generated the local similar pixels are searched in all the bands and the exploited for the noise free estimation of the image. Based on the spectral and the spatial details acquired in the previous stages the noise free estimation of the image is done by adding the filtered noise back to the denoised version.

Our experimental results are shown below.

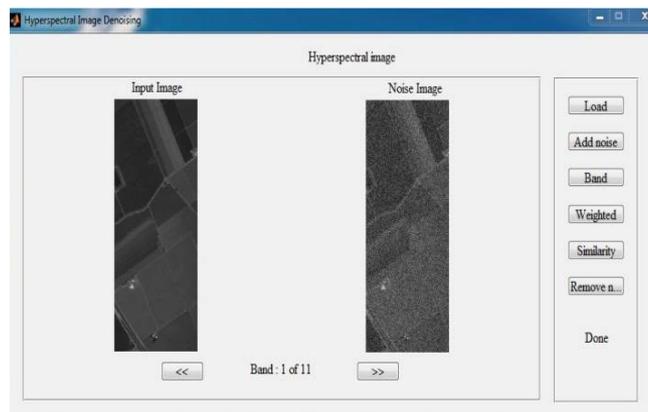


Fig 2: Loading HSI with different bands

The above screenshot shows that the HSI is loaded with different bands. This can be verified from the statement “Band: 1 of 11”. The above image has 11 bands and these bands are all different from each other. Similarly, the noisy image also has the different set of bands. Every time the push_button is hit, the band number either increases or decreases and thereby providing the real look of the HSI. This step plays a major role in the project as this is the very first step that we will be following. So, there should not be any error in the loading phase of the project.

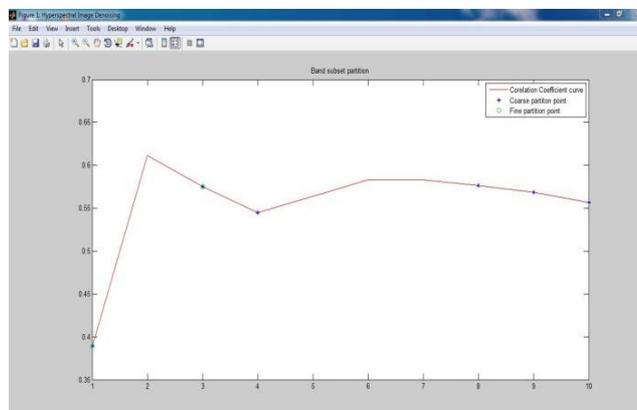


Fig 3: Band Subset Partition of the HIS

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The above screenshot shows us that the Correlation coefficient curve needs to be plotted in order to find the local similar pixels. Based on the SNR in the previous screenshot, we see that the partition needs to be done like the coarse partitioning, which gives the coarse partition points and the fine partitioning gives the fine partitioning points.

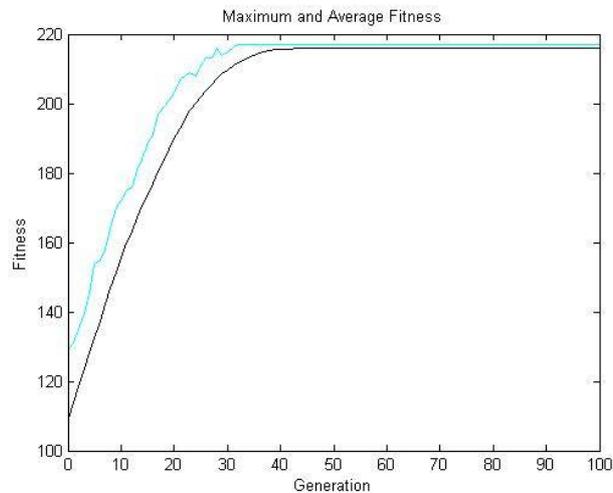


Fig 4: Average and Maximum Fitness graph

The above screenshot shows the graph for the Fitness vs. Generation. This also has the graph which shows for every band there is a 100 generation and each generation will have the average and the maximum fitness. The average and the maximum fitness curve are calculated and this will be assigned to the band. This weighted average will have to be passed on to the next level for the similar local pixel searching.

Check the similarity pixel in Band : 10

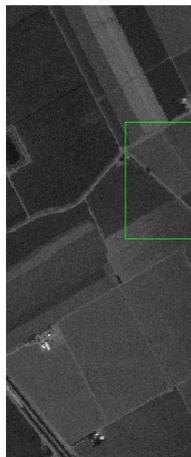


Fig 5: Searching for similarity pixel

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The above screenshot shows us that in every spectral band the spatial similar pixel searching needs to be done. In every band the similar pixel is compared with the previous band and marked as similar pixel. These similar pixels are marked using a green border in the project.

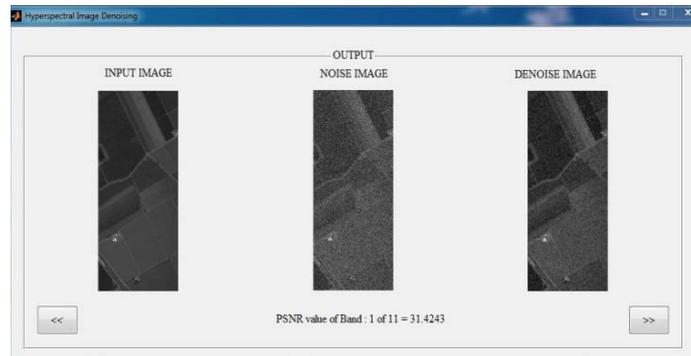


Fig 5: Denoised image for noise 0.01 SNR

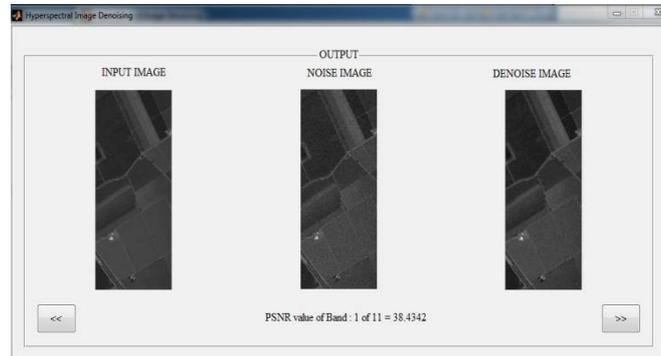


Fig 6: Denoised image for noise 0.02 SNR

The above two screenshots show the denoised image for the different SNR of 10 and 20. The denoised HSI can be seen in the above two screenshots. The print statement PSNR of the image tells us that the Peak signal to noise ratio. The values of PSNR will be different for different noise ratios.

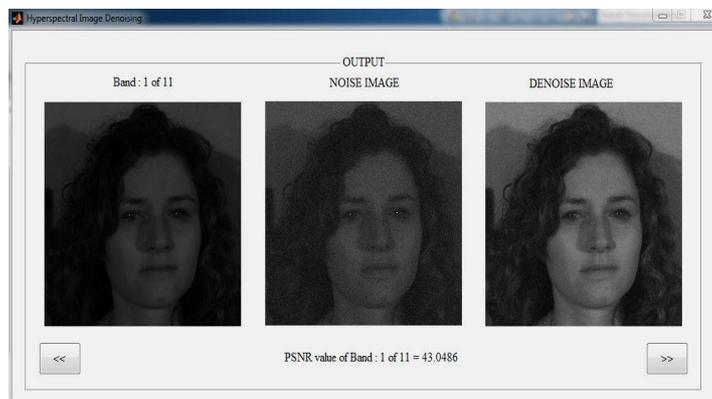


Fig 7: Denoised image for face taken at 1m distance

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The above screenshot shows the denoised image for the face, which is taken from a distance of 1m. The PSNR for the above screenshot shows that it the value is 43.0486 which is using the concept of the GAs. So we can see a major increase in the PSNR value when compared to the traditional systems. The HSI, which is captured at a distance of 1m is having a clear and distinguished features and that would best suit for our application.

IV. CONCLUSION

In this project, the method of denoising the HSI has been done using the Spectral Spatial Adaptive Sparse Respresentation technique. This involves the usage of both the spectral fields and the spatial fields. Hence, the amount of noise that is removed is better when compared to all the available techniques of denoising the HSI. This has been proved with the above implementation and results and also validated. Therefore, the project has been completed successfully with the desired outcomes.

The main aim of this project is to eliminate Gaussian noise. There might be other types of noise involved in the image like impulse noise, shot noise, uniform noise and so on. Eliminating such other types of noise will be the future enhancement of the project. Apart from this, by applying optimization algorithms to various modules, the PSNR can be enhanced.

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