A Review on Hyperspectral Image Denoising

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***Abstract*-This paper represents various methods of minimizing noise from Hyperspectral images. This work addresses the issue of minimizing mixed noise from Hyperspectral images in particular a mixture. The denoising has been analysed as an optimization problem solution to which has been given by split-Bregman approach. Experimental results explain that the proposed algorithm can decrease significant amount of noise from real noisy hyperspectral images compared to existing state-of-the-art techniques.**

Keywords- hyperspectral images, denoising, split-Bregman approach, optimization.

I. INTRODUCTION

Images which are captured over hundreds of bands of electromagnetic spectra and ranging from around 400 to 2500 nm are known as hyperspectral images. Hyperspectral images attract more and more interest in present era in different domains, such as geography, security, farming and military. They use the HSI for the target detection or classification to find objects or materials of attraction on the land.

Unfortunately, in the seized process, the HSI is mainly damaged by various types of noise, such as thermal noise, photonic noise and strip noise. HSI is the mixture of Gaussian noise and sparse noise. The sparse noise includes random valued impulse noise, salt-and-pepper noise, and horizontal and vertical deadlines. The line stripping problem mostly occurs when sensors goes out of radiometric calibration. Sparse noise is the noise which corrupts only few pixels in the image but corrupts them heavily. Images are corrupted by noise due to several reasons, including fluctuations in power supply, dark current. Therefore, denoising methods have become an unfavourable step for improving the successive target detection and classification in remote sensing imaging applications.

The data of Hyperspectral images has very high resolution and spatial resolution is very low than the data attained from other type of sensors. The low spatial resolution has vast applications. There are various factors by which we can distinguish hyperspectral and multispectral images. The hyperspectral image contains more than a hundred images whereas the multispectral has three at ten images. The spectral resolution of HIS images is nearly hundred and multispectral value is ten. The band of HIS images is consider to be regular and for multispectral images it is irregular and large. The various techniques for hyperspectral denoising are low-rank matrix recovery (LRMR), Principal component analysis (PCA), Un-mixing-based Denoising (UBD), Spatio-Spectral Total Variation (SSTV) [1] [2].

HIS data consists of set of vector that are associated with a given spatial position or pixel. In the given fig.1 gray scale image is also called band image which is represented by the spectrum for the given pixel. Thus different pixels will have different spectra.

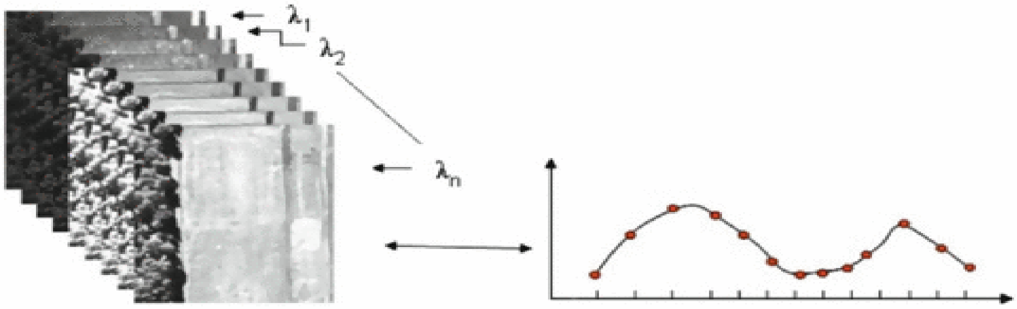

Fig 1.HSI as a series of gray scale image and spectrum over the wavelength [1].

II. LITERATURE REVIEW

In Feb 2006, H. Othman and S. Qian explained that analysis is based on the paradigm of the nature immune systems, Unsupervised Artificial Immune Classifier (UAIC). The UAIC is used for classifications of multi/hyperspectral remote sensing images. The main mechanisms and concepts used in UAIC include antibody population evolution, clonal selection and memory cell development. The experimental shows that the proposed UAIC has high classification accuracy. The analysis with different types of images is made and found that the average overall clarity and Kappa coefficient are raised [3].

In July 2008, Damien Letexier and Salah Bourennane used bi-dimensional straight-line detection algorithm which is used to flatten the HSI tensor. It improves the signal to noise ratio and the signal subspace dimension is reduced. This technique provides better performance while restoring impaired HYDICE HSI. In contrast to outcomes on real-data HYDICE images shows that the tensor description permits a superior restoration compared to channel-by-channel denoising or to PCA–SWT wavelet thresholding technique. Multidimensional Wiener filtering (MWF) works mainly for small goals those are not parallel to rows or columns [4].

In 2009, Begüm Demir, Sarp Ertürk and M. Kemal Güllü suggested Empirical Mode Decomposition (EMD) analysis followed by wavelet shrinkage denoising in hyperspectral image to improve the classification accuracy. This approach is used to explain the analysis of nonlinear and non-stationary data and adaptively decay the signal into Intrinsic Mode Functions (IMFs). In this method firstly, 2D-EMD is tried on hyperspectral image band and IMFs are acquired. Then, the wavelet shrinkage denoising method is used to denoise the first IMF of each hyperspectral image band and the sums of bottom order IMFs with the denoised first IMF are used as new characteristics for classification with Support Vector Machine (SVM). Test solutions tells that utilization of denoising of the first IMF Provides better SVM classification accuracy [5].

In January 2010, L. Zhang and X. Huang recommended that to calculate the clarity of classification the research calculate the complete clarity by contrasting the classified image with real investigated map. The results show that over all accuracy had been increased by 7% and the accuracy of easy mixed classified objects is more than 20% [6].

In October 2010, S. Bourennane, C. Fossati, and A. Cailly urge that adaptive multi-dimensional Wiener filtering (AMWF) can performs both spatial filtering and spectral dimensionality reduction (DR). Advantage of using this technique is that it permits the extraction of spectral components by taking into account spatial information as well as time estimating spatial filters to denoise them. In contrast with selected hybrid filters, which can perform two dimensional spatial filtering of the spectral components this technique has an application of classification in corrupted data [7].

In March 2011, Guangyi Chen and Shen-En Qian proposed that by using principal component analysis (PCA) hyperspectral cubes that have a good signal-to-noise ratio by removing the noise in the low-energy PCA output channels. The proposed denoising method in this paper utilizes the PCA to de- correlate the fine features of the data cube. A 2-D bivariate wavelet threshold is used to clear away the noise for low-energy PCA channels, and a one dimensional dual-tree complex wavelet transform denoising analysis is used to erase the noise of the spectrum of each pixel of the data cube [8].

In May 2012, Peng Liu, Fang Huang, Guoqing Li, and Zhiwen Liu explained a method for remote-sensing images based on partial differential equations. This technique indicates the resemblance between the various band images in a multicomponent image. In this method if denoising is done on the original data cube, then the fine features in the data cube could be lost [9].

In January2014, Daniele Cerra, Rupert Muller, and Peter Reinartz suggested that unmixing-based denoising is a direct method representing any pixel as a straight combination of credit spectra in a hyperspectral scene that can easily remove noise effectively for spectral bands with small and large noise effectively signal-to-noise ratio. The drawback of the method is that it needs a reasonably large number of pixels for each reference spectrum in order to derive a meaningful mean value robust to noise and local variations. Unmixing-based Denoising (UBD), a method is based on the statistical properties of the spectrum where as traditional algorithms depend on second-order statistics, UBD constructs a single spectrum of noise-free reference spectra with which we can reconstruct bands with low SNR and certain degree of reliability [10].

In August 2014, Hongyan Zhang, Wei He, Liangpei Zhang and Huanfeng Shen used the new restoration technique called low-rank matrix recovery which can remove the Gaussian noise, impulse noise, deadlines, and stripes at the same time. There is no spatial constraint imposed on the neighboring pixels of the HSI, which may cause an undesirable presentation for very large areas of absent pixels [11].

In January2015, Hemant Kumar Aggarwal and Angshul Majumdar demonstrate that images get corrupted by various noises during acquisition process. To overcome this Split-Bregman based approach which also solve resulting optimization problem is suggested. Proposed fusion initial algorithm is able to achieve higher PSNR and SSIM values contrast to other methods. The quality of restored hyperspectral image by explained algorithm is better than the sate-of-the-art algorithm. Experimental results indicate that our proposed method is about 4.5 dB better in PSNR and 40% better in SSIM [12].

In January 2016, Hemant Kumar Aggarwal and Angshul Majumdar used an algorithm based on spatio-spectral total variation that not only removes the Gaussian noise but also sparse noise. A general noise model has been considered which accounts for not only Gaussian noise but also sparse noise. The quantitative and qualitative results demonstrate the superiority of the proposed algorithm in terms of peak signal-to-noise ratio, structural similarity, and the visual quality. The denoising issue has been developed as an optimization problem results has been obtained from split-Bregman. Experimental results represent that the explained algorithm is able to reduce noise from real noisy hyperspectral images [13].

Table 1. Comparison of PSNR Values Obtained by different algorithms for different kinds of mixed noise [13].

MIXED NOISE	PEAK TO SIGNAL NOISE RATIO (dB)					
	NOISY	HTV	PCAW	LRMR	GSP	SSTV
Gaussian (SNR=20)	30.29	35.18	40.44	39.98	36.86	41.12
Gaussian (SNR=20) + impulse (5%)	17.01	25.84	30.81	35.12	33.55	40.38
Gaussian (SNR=20) + impulse (10%) + 4 horizontal & 4 vertical lines	14.17	21.14	25.99	27.59	32.96	39.88

Table 2. Comparison of SSIM Values Obtained by different algorithms for different kinds of mixed noise [13].

MIXED NOISE	STRUCTURAL SIMILARITY INDEX					
	NOISY	HTV	PCAW	LRMR	GSP	SSTV
Gaussian (SNR=20)	0.90	0.93	0.99	0.98	0.97	0.99
Gaussian (SNR=20) + impulse (5%)	0.52	0.78	0.90	0.97	0.95	0.98
Gaussian (SNR=20) + impulse (10%) + 4 horizontal & 4 vertical lines	0.33	0.59	0.83	0.87	0.94	0.98

III. CONCLUSION

A general noise model is taken which accounts for not only Gaussian noise but also sparse noise. The denoising problem has been formulated as an optimization problem which is overcome by split-Bregman approach. This algorithm is able to achieve higher PSNR and SSIM values compared to other techniques. The visual quality of restored hyperspectral by this technique is better than other methods.

ACKNOWLEDGMENT

I owe an intellectual debt to my worthy guide Er. Bhawana Utreja and co-guide Er. Jaspreet Singh Kaleka for their timely support, suggestions and inspirations. I sincerely thank my friends behind this endeavour. All round assistance of my family in promoting this endeavour at every step cannot be forgotten.

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