DENOISING OF HYPERSPECTRAL IMAGES USING BLOCK MATCHING AND 3D FILTERING

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ABSTRACT : *Hyper spectral remote sensing images have been widely used in countless applications, owing to their remarkably high spectral resolution (hundreds or thousands spectral channels), which enables precise material identification via spectroscopic analysis. The applications include earth observation, environmental protection and natural disaster monitoring. However, this potential is often compromised due to low quality of the HSIs, linked with various degradation mechanisms, such as electronic noise, Poissonian noise, quantization noise, strippe noise, and atmospheric effects. In this project a fast Hyperspectral image denoising scheme is proposed.*
Keywords*:* Hyper spectral image, electronic noise, poissonian noise, strippe noise

1. INTRODUCTION

Hyper spectral imaging, like different spectral imaging, collects and techniques records from throughout the electromagnetic spectrum. The purpose of hyperspectral imaging is to gain the spectrum for every pixel withinside the photograph of a scene, with the reason of locating objects, figuring out materials, hyperspectral images are used to find inside of an image by using the suitable and denoised detecting techniques.

There are fashionable branches of spectral imagers. There are pushbroom scanners and the associated whisk broom scanners, which study snap shots over time, and photo hyperspectral imaging, which makes use of a staring array to generate an photograph in an instant. Whereas the human eye sees colour of seen mild in commonly 3 bands (lengthy wavelengths - perceived as red, medium wavelengths - perceived as green, and brief wavelengths - perceived as blue), spectral imaging divides the spectrum into many extra bands.

2. LITERATURE SURVRY

Images that are captured over masses of bands of electromagnetic spectra and starting from round four hundred to 2500 nm are referred to as hyperspectral pics. The use the HSI for the goal detection or class to locate gadgets or substances of enchantment at the land. Unfortunately, withinside the seized process, the HSI is specifically broken through numerous forms of noise, inclusive of thermal noise, photonic noise and strip noise.

HSI is the combination of Gaussian noise and sparse noise. The sparse noise consists of random valued impulse noise, salt-and-pepper noise, and horizontal and vertical deadlines. The line stripping hassle mainly happens whilst sensors is going out of radiometric calibration. Sparse noise is the noise which corrupts handiest few pixels withinside the photo however corrupts them heavily. Images are corrupted through noise because of numerous reasons, which include fluctuations in electricity supply, darkish current.

The records of Hyperspectral pics has very excessive decision and spatial decision could be very low than the records attained from different kind of sensors. The low spatial decision has considerable applications. There are different factors through which we are able to distinguish hyperspectral and multispectral pics. The band of HIS pics is recollect to be normal and for multispectral pics it's far abnormal and large. The numerous strategies for hyperspectral denoising are low-rank matrix recovery

(LRMR), Principal thing analysis (PCA), Un-mixing-primarily based totally Denoising (UBD), Spatio-Spectral Total Variation (SSTV)

3. IMAGE DENOISING

All virtual pictures incorporate a few diploma of noise. Often instances this noise is brought through the digital digicam while a image is taken. Image denoising algorithms try to eliminate this noise from the picture. Ideally, the ensuing denoised picture will now no longer incorporate any noise or introduced artifacts. Major denoising strategies encompass Gaussian filtering, Wiener filtering, and wavelet thresholding. Many greater strategies had been developed; however, maximum strategies make assumptions approximately the picture which can cause blurring.

This will provide an explanation for those assumptions and gift a brand new technique, the non-neighborhood approach set of rules that doesn't make the equal assumptions. The non-neighborhood approach technique will then be as compared to different denoising strategies the use of numerous measurements at the output pictures. One of the measurements used may be the technique noise, that is the distinction among the picture and denoised picture.

4. EXISTING METHODS

Identical thoughts were pursued in multi-band picture denoising: BM4D, VBM4D, and MSPCA-BM3D use collaborative filtering in agencies of 3-D patches extracted from volumetric data, videos, multispectral data, respectively.

Most of the posted hyperspectral denoising algorithms are time-consuming, specially because of the big sizes of HSIs and, often, because of the implementation of iterative estimation strategies each withinside the spatial and the spectral domains.

4.1 Previous methods and motivations

Most denoising algorithms make assumptions approximately the noisy picture. These assumptions can motive blurring and lack of element withinside the ensuing denoised pics. The first assumption is that the noise contained withinside the picture is white noise. This manner that the noise consists of all frequencies, low and excessive. Because of the better frequencies, the noise is oscillatory or non-easy. The 2nd assumption is that the authentic picture (picture without the noise) is easy or piecewise easy. This manner the authentic picture or patches of the authentic picture handiest comprises low frequencies. Previous techniques try to separate the picture into the easy part (authentic picture) and the oscillatory part (noise) with the aid of using doing away with the better frequencies from the decrease frequencies. However, now no longer all pics are easy.

Images can comprise great information and systems that have excessive frequencies. When the excessive frequencies are eliminated, the excessive frequency content material of the authentic picture could be eliminated at the side of the excessive frequency noise due to the fact the techniques can not inform the distinction among the noise and authentic picture. This will bring about a lack of great element withinside the denoised picture. Also, not anything is achieved to get rid of the low frequency noise from the picture. Low frequency noise will continue to be withinside the picture even after denoising. Because of this lack of element Baud's et al. have advanced the non-neighborhood manner algorithm.

5. PROPOSED METHOD

Let the Hyperspectral image with n vectors is denoted by X which is given as X = [x1, x2, …. xn]. The rows of the hyperspectral image contain, say, m number of spectral bands in the form of images. These images corresponds to the reflectance in wavelength interval with n pixels ordered in an

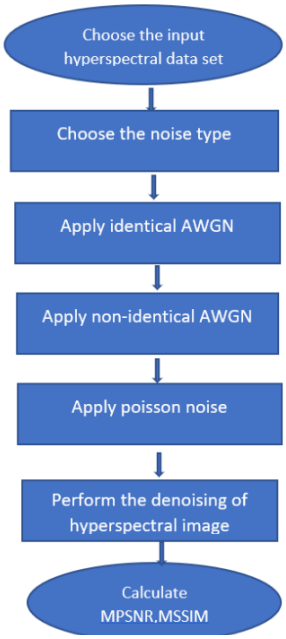
image manner. The modelling of noise effect in hyperspectral images is given as Y = X + N . where Y is the read hyperspectral image data, X is the intended original hyperspectral image data and N is noise. The original hyperspectral image now can be defined as X = VZ .The matrix Z corresponds X with respect V. The matrix V is a semi-unitary matrix. Hence VTV = Ip.. The real world images are self-similar. It means that the images contain very close parts at different spots and levels.

The analysis of this self-similarity is crucial to design and implement any image inverse problem. Moreover, as each and every band refers to reflectance, of the same surface. Also, the structure of self-similarity is similar over all bands. As V is semi-unitary, Z = VTX It is already shown that when the eigen images are self-similar, then non-local patch based methods can be used to perform denoising. Now consider additive Gaussian noise with zero mean and which is independent and identically distributed over all parts. The eigen images in denoising are articulated as

5.1 Tools used

- Data acquisition Toolbox
- DSP system Toolbox
- Image processing Toolbox
- Signal processing Toolbox

5.2 Flowchart



6. SIMULATION RESULTS

Two datasets are considered. Dataset – 1 is of 103 bands each with 200x200 image. Dataset – 2 is of 191 bands each with 256x256 image. The noise considered are Gaussian and Poissonian. Three categories of noise are considered with different levels in each category.

In category – 1, Gaussian noise with 5 different levels of standard deviation is considered, where at a time same deviation will be applied to all the bands. These are 0.04, 0.08, 0.12, 0.16 and 0.2.

In category – 2, non-identically distributed Gaussian noise is selected. The standard deviation of noise component is set to vary between 0 and 0.2 to the bands randomly.

In category – 3, Poisson noise is applied to the bands in a non-identical manner, but in all the cases the noise is so added such that the initial signal to noise ratio is 10dB. The band 40 of original hyperspectral images are shown in Fig.

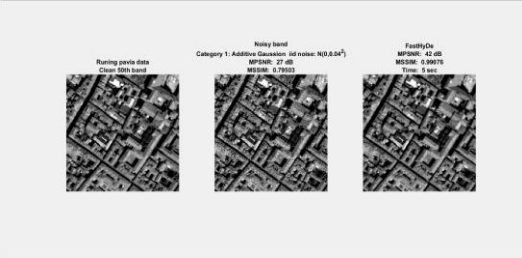


Fig.6. Simulation results depicting input image, noisy and reconstructed versions

Table : Performance assessment and comparison of proposed technique

			Noisy	BM3D [6]	BM4D [7]	MSPCA-BM3D [8]	NAILRMA [9]	PROPOSED
HSI - 1	σ = 0.04	M-PSNR	26.45	32.68	39.98	37.03	41.31	41.52
		M-SSIM	0.795	0.9212	0.9832	0.9632	0.9874	0.99076
	σ = 0.08	M-PSNR	21.95	29.11	35.55	30.93	36.8	38.33
		M-SSIM	0.54	0.835	0.9556	0.8753	0.9646	0.98
HSI - 2	σ = 0.04	M-PSNR	26.45	31.97	39.7	40.8463	43.1575	44.81
		M-SSIM	0.795	0.9166	0.984	0.9845	0.992	0.99
	σ = 0.08	M-PSNR	21.95	28.33	35.03	34.79	38.22	40.08
		M-SSIM	0.54	0.8253	0.9536	0.9435	0.9769	0.99

The above table shows that the comparision of denoising algorithm with the techniques in literature. The techniques are BM3D, BM4D, MSPCA-BM3D AND NIALRMA

7. CONCLUSION

In this project, a denoising of hyperspectral images based on eigen-matrices is presented. The spectral vectors associated with the clean hyperspectral image will lie in a p-dimensional subspace. A semi-unitary matrix is then defined which will have an association with a matrix whose rows form an image called eigen image. This association actually results in forming the clean hyperspectral image. The estimation of this matrix is central to this technique. The images associated with the rows of this matrix are shown to be self-similar. Hence this matrix is estimated using the well-known BM3D.

The proposed method is verified by taking two spectral sequences into consideration. Gaussian and Poisson noises are applied. The calculated MPSNR and MSSIM clearly show a notable improvement by the proposed technique when compared with the existing methods.

8. FUTURE SCOPE

In this project, self-similarity among the neighbouring pixels of a plane is considered. investigations may be carried out to verify the possibility of exploring the self-similarity among planes

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