Decomposable Pixel Filter Algorithm for Multispectral Satellite Image Denoising

Pragati Jha
Shri Shankaracharya Group of Institutions, Bhilai

G.R.Sinha
Shri Shankaracharya Group of Institutions, Bhilai

ABSTRACT

The multispectral images (MSI) convey high definition and authentic representation of the real world in comparison with the RGB or gray-scale images. MSI images help improve the performance measures for image processing and related information encoding tasks. Although, MSI images are often prone to corruption by various sources of noises either while procuring the images or during transmission. This paper studies an innovative MSI de-noising technique which is based on learning based morphology of bidirectional recurrent neural network. The algorithm used in the technique filters the inhomogeneous noisy pixels and the neighboring pixel bands with the noisy patches are corrected accordingly.

Keywords

Multi Spectral Image (MSI), Image De-noising, Spatial Regularity, Satellite Imagery, Noise Removal.

1. INTRODUCTION

The light reflectance and illumination of natural world scene is embedded with a wide stretch of array for each multi-spectral band. The MSI imaging system records the same with the aid of multi-spectrum arrays of sensors to record the multi-spectral signal. MSI images are different than standard RGB images in a sense that the usual multispectral images (MSI) convey an authentic representation of real world scenes, and hence the performance measures of remote sensing operations are enhanced. However, MSI imagery is often influenced noisy signals and thereby corrupting to the original image. Such noises can be due to the limitations of recording equipment, ranged sensitivity of sensors, calibration error and photon effects [1, 2]. Moreover, narrow bandwidth and insufficient radiance energy increases the probability of the pixel being influence by thermal noises significantly, where the energy obtained through the sensors might be low and prone to variation. These noises are inevitable to cope up with the satellite based remote sensing environment [3-5].

Generally, MSI imaging system consist of huge spectral redundancy [4], which implies towards the fact that the obtained image for a range of wide bands are correlated with each other; and the noise removal takes place as elimination of minor components of spectrum information [6-8]. Thus, denoising of MSI image remains a challenging task because of lack of robust approach. There are three basic approaches normally employed for denoising MSI images:

- 2D classical approach such as NLM (Non Local Means), K-SVD (K means-Singular Value Decomposition) and BM3D (Block Matching and 3D Filtering) [9-11] which works by using the correction algorithms applied over an image over several bands.
- Tensor based noise elimination which uses tensor factorization and can be considered as an extended form of multi-way filtering method involving Tucker factorization [4,12].The method proposed by Liu et al.[13,3] also have also produced good results but the performance is sensitive to noise types and ranges.
- By constructing small 3D cubes and then rendering it for noise removal [14]. This employs 3D cube based approach [8, 15].

2. LITERATURE SURVEY

Multispectral Imagery (MSI) is steadily growing in popularity as a digital means for remote sensing, detection of thermal signature and terrain analysis. It is commonly used as a feasible substitute for mapping applications when standard mapping & geodesy products are outdated or inadequate. The ability to record spectral reflectance in different portions of the electromagnetic spectrum is the primary & foremost attribute of MSI, which can be useful in a number of applications. However, thermal effects, sensor saturation, and transmission errors generate a noise that deteriorates the quality and are also affected by multiplicative noise in addition to additive noise; thereby creates a bad effect on image analysis.

Generally, the characteristics of such noises influencing the images depend on the type of the image to be processed and on the system of acquisition. This type of noise can be represented as a normal distribution (Gaussian), zero-mean random process which requires continuously varying thresholding based on the dependency between magnitude quaternionic coefficients in local neighborhoods and phase regularization through Gabor filters. Ultimately, noise reduction is mainly involves hours of tedious manual work to process by the researchers to put forth the denoised image for further analysis. The block-matching & BM3D algorithm is one of the high performance and an effective techniques for MSI denoising [16-19]. In addition with the Color BM3D algorithm meant for standard RGB images trailing the method based on luminance chrominance color transformation is applied over RGB data in order to exploit the self-similarity for structurally shared by the three color components [16, 20]. This requires a locally adaptive data driven spectral manipulation, where a basic approach to this problem, was assessed by several authors [21-25,27,29]; it meant to derive spectral components and its inter correlation through the method of finding principal component analysis[26,27].

Thus, in the study we summarize several denoising algorithm for the scenario of multi-spectral image denoising using several statistical and learning based techniques; for which its performances is measured based on the two factors such as its computational workload and the denoised output image which readily aid the users in the process to use the well-known algorithms for detection, segmentation, and classification.[30,31] The study tend to give a very good division of the coefficients in terms of magnitude and three-phase angles to generalizes better the concept of analytic signal to image promises an easy transformation for the analysis and processing of multispectral images with strong structural information. Furthermore, we've also discussed the property of multi-spectral images such as shift invariant and directivity. The Multispectral database is used for MSI image during the study [28-29,32].

3. Decomposable Pixel Filtration Analysis Algorithm

Decomposable Pixel Filter Algorithm (DPFA) for MSI images de-noising are used in the process of de-noising for multispectral images by applying bi-directional recurrent neural network. The performance is based on two major factors viz. computational load for the algorithm wherein the use of recurrent neural network makes it learning based algorithm; and the effective parameterization of the variant noisy signals to achieve a good division of saturation coefficients in order to automatically adjust the magnitude of phases for the analytical signal which gives strong structural information for a regularized signal to noise ratio (SNR). The steps of the algorithm are:

Input: Noisy Image I

Output: Denoised Image I'

Step 1: Apply the filter function *f( )* to m x n pixels of image I; where function 'f' is given as:

$$f = arg \sum_{i=1}^{m} \sum_{j=1}^{n} \varphi_{i,j}^{C} . \sigma \| \mathrm{a_i} - \mathrm{b_j} \|_{n}^{m} \quad (1)$$

where, $\varphi_{i,j}^{C}$ degree of membership of $\mathrm{a_i}$ in cluster set $\mathrm{b_j}$; $\mathrm{a_i}$ is the multidimensional data block ; $\mathrm{b_j}$ is the center of the cluster of the cluster of multi dimensional data blocks for the congregated pixel position; σ is a scalar weighted by the regularization term derivable by the disparity of homogeneity within the cluster C for the timed interval of pixels m and n.

Step 2: Return the update value of the threshold for the pixel position x, y:

$$t(i,j) = \sum_{m=1}^{n} \frac{f_{i,j+1}^{2}}{f_{I+1,j}^{2}} \quad (2)$$

Step3: Initialize iterative filtration:

$$\sum_{i=1}^{c} \varphi_{i,j} = \begin{cases} 1, & \mathrm{b_j} = \dfrac{\sum_{i=0,j=1}^{n} \varphi_{i,j}^{2} \mathrm{a_i}}{\sum_{i=0,j=1}^{n} \varphi_{i,j}^{2}} \geq t \\ 0, & \mathrm{b_j} = \dfrac{\sum_{i=0,j=1}^{n} \varphi_{i,j}^{2} \mathrm{a_i}}{\sum_{i=0,j=1}^{n} \varphi_{i,j}^{2}} < t \end{cases} \quad (3)$$

where, t is the threshold value.

Step 4: Use recurrent neural network while forming an aggregated homogenous matrix to speed up the next consequent process using machine leaning as:

$$h(T+1) = F\big(\tanh(\varphi_{i,j}) + \tanh(\varphi_{i-1,j-1} h(T))\big) \quad (4)$$

$$Y(T) = F\big(W_h h(T-1)\big) \quad (5)$$

where, h is the hidden unit; T is the time; tanh ( ) is the activation function of the neuron; Y is the output; and W_h is weight from the hidden unit.

Step 5: Repeat steps 1-3 to form an aggregate of homogenous matrix until the whole image traversed.

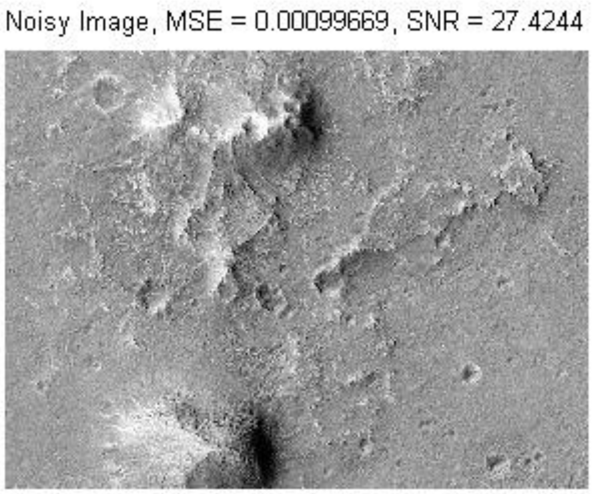


Figure 1: Noisy Image, I.

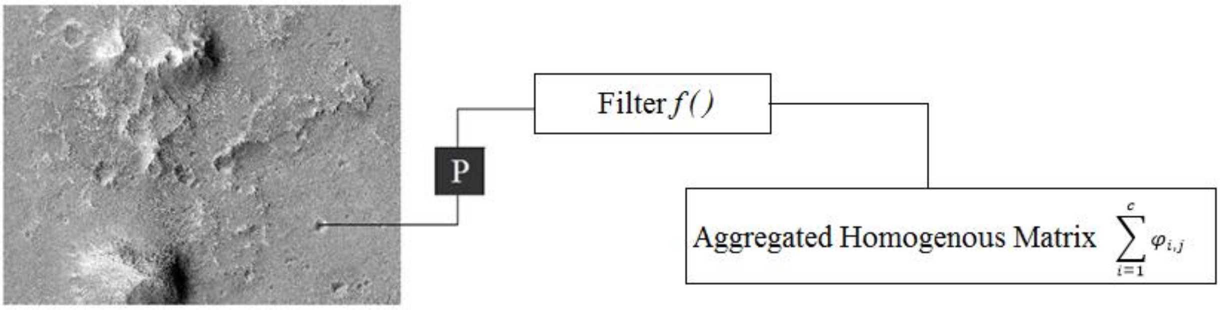


Figure 2: Determination of Neighboring Pixel Indices for P_i pixel Positions.

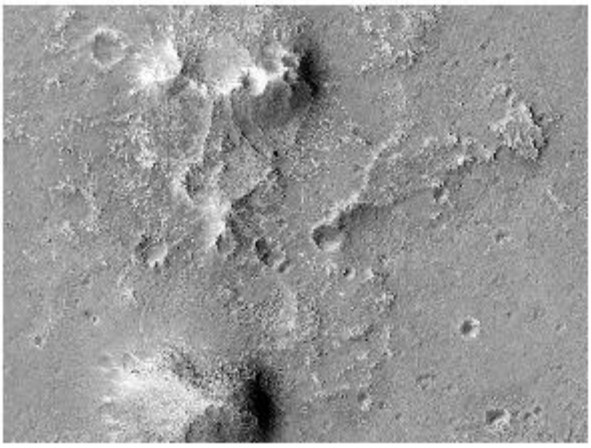


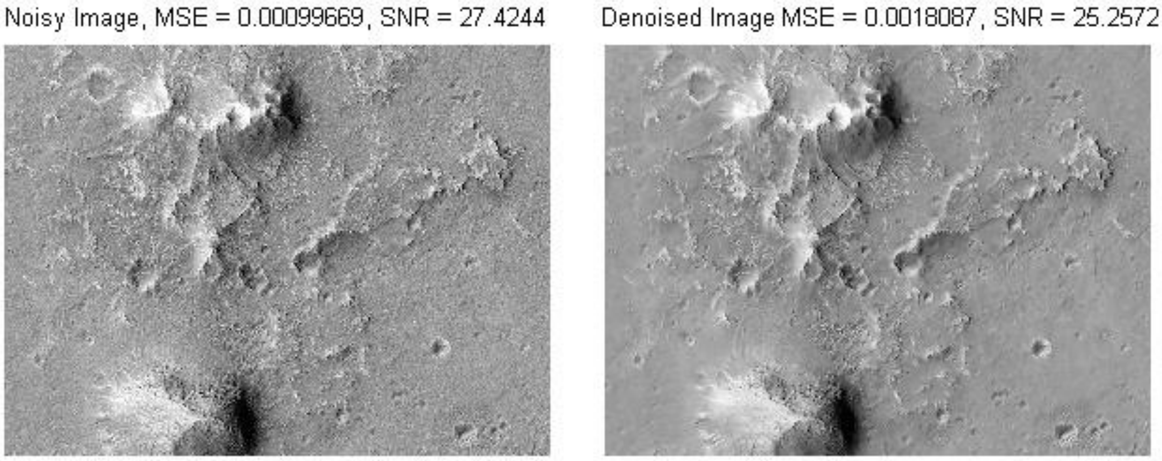
Figure 3: De-noised Image, I'.

Fig. 3 shows de-noised the image using DPFA. Fig. 1 shows an image which is raw MSI image.

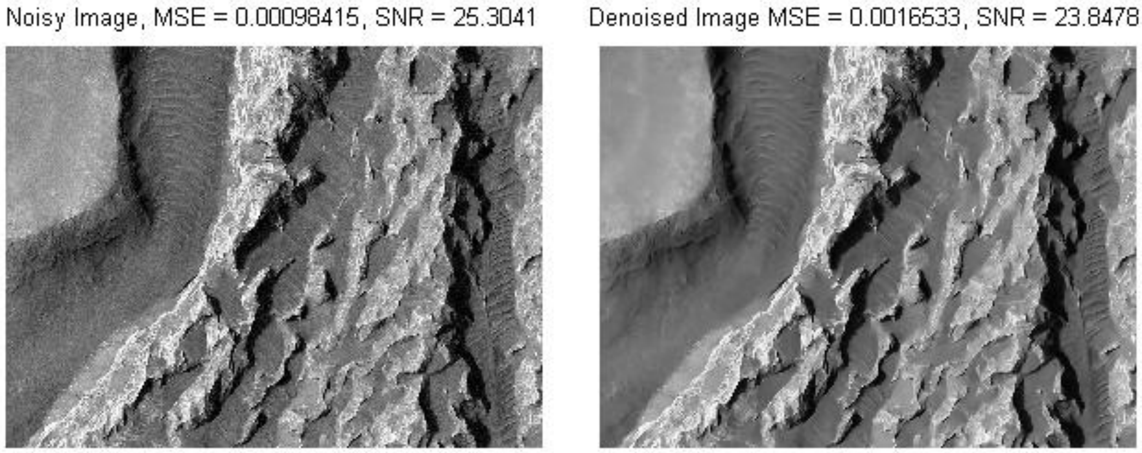
4. RESULT

Table.1. De-noising results of MSI images.

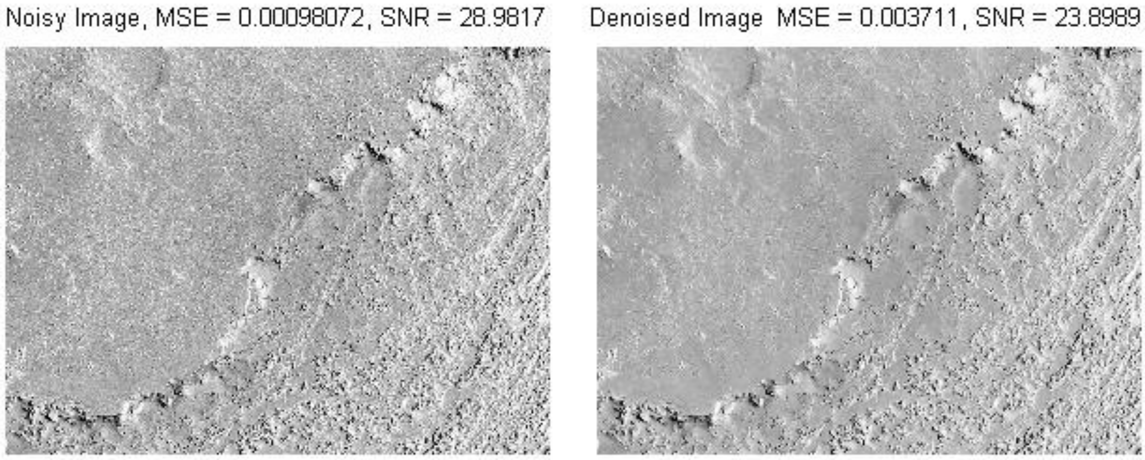
Image	Noisy Image		De-noised Image	
	MSE	SNR	MSE	SNR
1	0.00099669	27.4244	0.0018087	25.2572
2	0.00098415	25.3041	0.0016533	23.8478
3	0.00098072	28.9817	0.003711	23.8989
4	0.0010013	25.7159	0.00037186	31.3495
5	0.00074276	23.2035	0.00013993	28.3495
6	0.00083882	20.886	0.00010589	29.9232
7	0.00088107	18.7317	0.00016077	25.9367
8	0.0009948	15.7691	5.7354e-05	28.778
9	0.00098492	21.494	0.00019801	28.6501
10	0.00089379	16.2776	0.0032242	10.9822



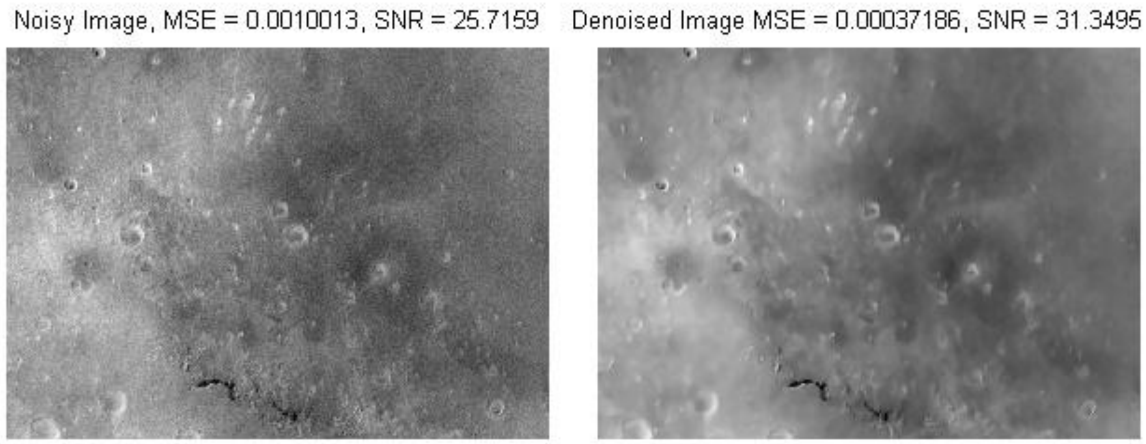
(a) MSI image Denoising of Lunar image.



(b) MSI image Denoising of Mars image



(c) Sample Test MSI image Denoising of Mars image



(d) De-noising of lunar image
Figure 4: Sample results of DPFA.

It can be seen in Fig. 4 that the noise of the MSI images is effectively filtered out with the help of DPFA algorithm effectively. We have studied a new DPFA algorithm for MSI de-noising which provides removal of the noisy pixels (see table 1). This method works on homogeneity of the spatial pixel distribution using recurrent neural network which is an effectively adaptive approach for multi-spectral bands. The performance for similar grouped sets gives the de-noising range of 89-92%. The aggregating and thresholding using DPFA helps achieve transformation directly from the noise influenced images. This method is an effective tool for the research works in the field of remote sensing or satellite imaging for automated MSI de-noising.

5. Conclusion and Future Scope

The performance of proposed denoising algorithms is gauged using quantitative performance measures such as signal-to-noise ratio (SNR), Mean Signal Error (MSE) as well as in terms of perseverance visual quality of the images. Among several of current techniques assume the noise model to be Gaussian or AWGN. In reality, this assumption may not always hold true due to the varied nature and sources of noise. Not all researchers use high value of variance to test the performance of the algorithm when the noise is comparable to the signal strength. Therefore, an ideal denoising method requires an all-round efficiency to actively reduce the noises from all sorts of noisy images while ensuring high throughput. Thus, most of the algorithms assume known variance of the noise and the noise model to compare the performance with different algorithms.

Use of cited filtering techniques has been restricted due to its limitations in providing sparse representation of data. Hence, the proposed DPCA is the best suited for performance because of its properties like sparsity, multi-resolution and multi-scale nature. In addition to performance, issues of computational complexity must also be considered. We didn't used the thresholding technique but the algorithm is principally based on the ABLATA algorithm and thereby adjust itself with the changing environment where the thresholding for dynamic values not prove to be beneficial for elimination of different noise types with the same method [30].

When using the proposed method it is emphasized that issue such as that of choice of primary resolution and choice of analyzing wavelet also have a large influence on the success of the shrinkage procedure. When comparing algorithms, it is very important that researchers do not omit these comparison details. It is expected that the future scope of our research will eliminates the users to resort to focus on statistical models which are primarily based on different scales of coefficients and manual parameterization.

The implemented method is robust for MSI Denoising. However, following works are proposed as future scope of the research work:

- Our proposed methodology finds a tuned balance of image feature preservation. Thus, we can employ this technique for in house satellite based denoising also.
- The image properties isn't compromised thus this technique shall be employed for image transmission of low resolution images for faster transmission and latter denoising at receiver's end to obtain the preserved quality of the actual image.
- It can be employed for denoising of images in remote sensing areas without manual intervention of consistent noise removal task.
- It can be used to quantize and compress images.

6. REFERENCES

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