ISSN:0975-9646

M.Vijay et al, / (IJCSIT) International Journal of Computer Science and Information Technologies, Vol. 3 (2) , 2012,3432-3435

Speckle Noise Reduction in Satellite Images Using Spatially Adaptive Wavelet Thresholding

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***Abstract*—This paper presents an efficient algorithm for removing noise in satellite images by combining Wavelet Thresholding, Total Variation in wavelet domain and Bilateral Filter, Joint Bilateral Filter (JBF) in spatial domain. During the first stage, the noisy image is passed through Bilateral Filter(BF) and some amount of noise is reduced but the image becomes blurred, hence adaptive wavelet thresholding is applied while applying the threshold rule, the important features in an image such as edges, curves and textures can be identified. In the third stage, Total Variation (TV) method is applied to wavelet threshold output denoised image. Also spatial domain method output provides a high quality denoising image than wavelet method with less artifacts, hence this wavelet domain output as a reference image for the Joint Bilateral Filter (JBF) .With the help of this reference image in the final stage and the non-linear combination of information of adjacent pixel, the edge details of the images can be preserved in a well manner. The experimental results prove that the proposed approach is competitive when compared to other denoising methods in reducing various types of noise. Also the proposed algorithm outperforms other methods both visually and in case of objective quality peak-signal-to-noise ratio (PSNR).The method also retains the edges and other detailed information very well.**

Keywords— **Image Restoration; Dyadic Wavelet Transform;Multiscale product Wavelet Thresholding;Joint Bilateral Filter.**

I. INTRODUCTION

The imaging devices which acquire or process satellite images introduce artifacts in those images. The images unruffled by different type of satellites are generally contaminated by different types of noises [1].Images denoising is done in prior of other image processing techniques.

Generally noises are produced due to imperfect instruments used in satellite image processing, problems with the data acquisition process, and interference, all of which can degrade the original content of the image. Furthermore, noise can be introduced by communication channels and compression also [1].

There are different types of noises that affect the digital images like dark current noise, Shot noise, Amplifier noise and quantization noise, and speckle noise. The Radar and satellite images are mostly inherent with speckle noise which is produced because of the variation in backscatter from inhomogeneous cells. The speckle noises are generated by radar waves that constructively or destructively produce light and dark pixels in an image. The overall noise characteristics in an image depends on many factors, which include sensor type, pixel dimensions, temperature, exposure time, and ISO speed [2].

Image coefficients concentrate on low frequency components whereas the noise has both low as well as high frequency components. The high-frequency components can easily be removed, whereas it is a challenging task to eliminate low frequency noise as it is difficult to distinguish between real data and low-frequency noise. Most of the natural images are assumed to have additive white Gaussian noise. Speckle noise [3] is observed in satellite images. Thus, denoising is the initial step to be considered before analyzing the image data. An efficient denoising technique is used to compensate for any data corruption .The goal of denoising is to remove the noise while preserving the important image details as much as possible.

The most common technique used in the denoising process is the Bilateral filtering techniques [4], [5]. It assist in sustain the edge details by suppressing only the noisy coefficients. In this paper the bilateral filter is integrated with wavelet thresholding to provide denoising framework. For a noisy satellite image, there are some differences between the coefficients of original image and noise depending on its features. On using wavelet transform, most of the energy of the original image will be crushed into a few high frequency coefficients [6], [7].

The satellite image data is corrupted by speckle noise, the components that correspond to noise will be distributed among low magnitude high frequency components. Most of the low frequency noisy components are similar to image details. So, the only way to eliminate those noises is done by comparing all the coefficients with a threshold and cutting off the coefficients that have smaller values than the thresholds [8], [9].

Wavelet thresholding is the most successful method. In wavelet thresholding, an image is decomposed into approximation (low-frequency) and detail (high-frequency) subbands, and the coefficients in the detail subbands are processed via hard or soft thresholding [8], [9], [10], [11]. The hard thresholding removes (sets to zero) coefficients that are smaller than a threshold; the soft thresholding shrinks the coefficients that are larger than the threshold as well. The main objective of the wavelet thresholding is the selection of threshold value and the effect of denoising depends on the selected threshold: a bigger threshold will throw off the useful information and the noise components at the same time while a smaller threshold cannot eliminate the noise effectively. Donoho [8] gave a general estimation method of threshold, but it may not be efficient up to the expected level. Chang et al. [12] have used predictive models to estimate the threshold. It is a spatially adaptive threshold based on context modelling. In addition to this data-driven threshold for image denoising in a Bayesian framework [13] has been proposed.

But, in wavelet thresholding the major problem experienced is generally smoothening of edges. To overwhelm this drawback the Total Variation [14] is done at each subbands of wavelet thresholding. This algorithm is a constraint optimization approach. Lagrange multipliers are used to impose constraints. Iterative method results in blurring of image coefficients which is the main drawback with this method.

The wavelet domain use any one of the shrinkage methods like VisuShrink [15], SureShrink [8], Bayes Shrink [16] etc. The Bayes shrink method determines the Bayesian rule to calculate the threshold value all through the wavelet coefficients.

Wavelet thresholding results in directly applying spatially weighted averaging without smoothing edges. To done these two Gaussian filters have been combined; one works in spatial domain, the other in the intensity domain.

But herein this proposed work, the noisy image is passed through Bilateral Filter (BF) and some amount of noise is reduced but the image becomes blurred, hence adaptive wavelet thresholding and Total Variation (TV) [14] is applied in the next stage. With the help of this reference image, Joint Bilateral Filter (JBF) [17] is applied so that the edge details of the images can be preserved in an effective manner.

The experimental results proves that the proposed method could not only reduce the noise in a well manner but also preserving the edge details in an image while comparing with other spatial and transform domain methods.

The paper is organized as follows. Section II introduces Wavelet Transform, Wavelet Thresholding, Total Variation Bilateral Filter (BF) Joint Bilateral Filter (JBF) is discussed in Section III. In Section IV, Proposed Method is discussed. The Section V presents the experimental results and discussion while concluding remarks are given in Section VI.

II. Wavelet Domain Approach

A. *Wavelet Transform (WT)*

The wavelet transform always offering great design flexibility while trying to replace standard image processing techniques, wavelet transforms provides an efficient representation of the image by finely tuned to its intrinsic properties. By combining such representations with simple processing techniques in the transform domain, multiresolution analysis can accomplish remarkable performance and efficiency for many image processing problems. Discrete non redundant wavelet transform plays a major role in image analysis techniques. But after the decomposition stage it introduces some artifacts. However one best example of redundant representation is Dyadic Wavelet Transform.

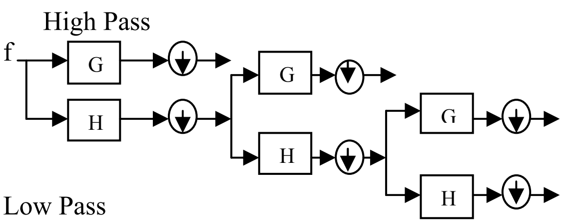


Figure 1 Image Decomposition (3 Level) using DWT

Here Wavelet Transform is considered as a Multiscale Edge Detector. It is computed by convoluting the input signal with dilated wavelet filters in a recursive manner.

B.Wavelet Thresholding

It has been noticed that in many images energy is mostly concentrated in a small number of dimensions with their coefficients relatively large compared to other dimensions or to any other images (specially, noise) that has its energy spread over a large number of coefficients. Hence, in wavelet thresholding, method each coefficient is thresholded (set to zero) by comparing against a threshold to remove noise, while retaining important image coefficients [24]. Usually two types of thresholding techniques are used soft and hard.

The hard thresholding operator is defined as

$$D(V, \lambda) = V \text{ for all } |V| > \lambda \qquad (1)$$
$$= 0 \text{ otherwise.}$$

Hard threshold is a “keep or kill” procedure and is more intuitively appealing.

The soft thresholding operator is defined as

$$D(V, \lambda) = 0 \text{ for all } |V| \le \lambda \qquad (2)$$
$$= \mathrm{sgn}(V)\,(|V|-\lambda) \text{ otherwise}$$

Soft thresholding results in reducing the coefficients above the threshold in absolute value.

Choosing the threshold value is crucial as larger value may result into loss of image information while smaller one may allow noise to continue.

The thresholding techniques also have disadvantages. In case of hard thresholding, they may not continuous at the threshold which may lead to the oscillation of the reconstructed image. In the soft thresholding case, there are deviations between image coefficients and thresholded coefficients which directly influence the accuracy of the reconstructed image. Another problem with this is retention of edge. Different edge detection algorithms are used to extract the contour feature of cell images. To overcome the edge retention problem the best opted method is bilateral filtering.

C. Total Variation

Total Variation is applied in wavelet domain to suppress noise.TV is an iterative step done to remove noise. This also has a drawback that iterative processing may sometimes result in blurring of image. The Wavelet domain results in the LL, HL, LH, and HH subbands. IDWT is done on wavelet coefficients which reconstruct the image with less noise at the edges.

The method of total variation is expressed as

$$v_t = \frac{\partial}{\partial a}\left(\frac{v_a}{\sqrt{v_a^2+v_b^2}}\right)+\frac{\partial}{\partial b}\left(\frac{v_b}{\sqrt{v_a^2+v_b^2}}\right) - \lambda\left(v - v_0\right) \qquad (3)$$

Where ‘λ’ is the tuning parameter. Larger value of λ gives
blurring effect to the image.

III. SPATIAL DOMAIN APPROACH

A. Bilateral Filter (BF)

Recently most popular denoising method is the bilateral filter [25]. The bilateral filter is a nonlinear weighted averaging filter and also the weights depend on both the spatial distance and the intensity distance with respect to the center pixel. The main feature of the bilateral filter is its ability to preserve edges while doing spatial smoothing. The bilateral filter is a robust filter because of its range weight, pixels with different intensities. It averages local small details and ignores outliers.

At a particular pixel location n, the bilateral filter output is calculated as follows,

$$\mathrm{I}'(\mathrm{n}) = \frac{\sum_{n\in N(n)} e^{-\frac{\|n-m\|^2}{2\sigma_e^2}} e^{-\frac{|I(n)-I(m)|}{2\sigma_c^2}} I(x)}{\sum_{n\in N(n)} e^{-\frac{\|y-x\|^2}{2\sigma_e^2}} e^{-\frac{|I(n)-I(m)|}{2\sigma_c^2}}} \quad (4)$$

The bilateral filter is also non-iterative and hence it achieves satisfying results with only a single pass. But it is has a problem with extreme outliers and blur effect.

B. Joint Bilateral Filter (JBF)

The important image features are preserved by wavelet-based denoising, so use this as a reference image, like the flash image in [23]. In this type of filter, the basic bilateral filter is modified to compute the edge stopping function using reference image. By this method, the edge-stopping function could be estimated more accurately. In the Joint Bilateral filter [24], the parameters, σ_c and σ_e vary with respect to the reference image quality and the noise level. At a particular pixel location n, the bilateral filter output is calculated as follows, Mathematically, at a particular pixel location v, the joint bilateral filter output is calculated as follows,

$$\mathrm{I}'(\mathrm{y}) = \frac{\sum_{x\in N(y)} e^{-\frac{\|y-x\|^2}{2\sigma_e^2}} H \;\; I(x)}{\sum_{x\in N(y)} e^{-\frac{\|y-x\|^2}{2\sigma_e^2}} e^{-\frac{|I(y)-I(x)|}{2\sigma_c^2}}} \quad (5)$$

Where $\quad \mathrm{H}= e^{-\frac{|J(y)-J(x)|}{2\sigma_c^2}}$

Here J represents the wavelet denoising reference image and $\sigma_c$determines the threshold value which varies in intensity from the central pixel according to the reference image. With the help of reference image, the denoising is performed. In the joint bilateral filter, the edge-stopping function is calculated as,

$$\sigma_c = \sqrt{\sigma_n} + 3 \qquad (6)$$

IV PROPOSED METHOD

In our proposed method, the noisy image is applied with thresholding rule so that the wavelet interscale dependencies are exploited to preserve edge structures while suppressing noise. An adaptive threshold is calculated and implemented on the on the wavelet coefficients and it provides better results the noisy image is passed through Bilateral Filter (BF) and some amount of noise is reduced but the image becomes blurred, hence adaptive wavelet thresholding is applied while applying the threshold rule, the important features in an image such as edges, curves and textures can be identified. In the third stage, Total Variation (TV) method is applied to wavelet threshold output denoised image. Also spatial domain method output provides a high quality denoising image than wavelet method with less artifacts, hence this wavelet domain output as a reference image for the Joint Bilateral Filter (JBF) .With the help of this reference image in the final stage the edge details of the images can be preserved in a well manner. The performance of the proposed image denoising algorithm and the reconstructed image quality are measured using Mean Squared Error (MSE) and Peak Signal to Noise Ratio (PSNR), given in equations (7) and (8) respectively.

$$MSE = \frac{1}{AB}\sum_{a=1}^{A}\sum_{b=1}^{B}(x(a,b) - \hat{x}(a,b))^2 \qquad (7)$$

$$PSNR = 10log\frac{255^2}{MSE} \qquad (8)$$

where $x(a,b)$ denotes the sample of original image and $\hat{x}(a,b)$ denotes the sample of distorted image. A andB are number of pixels in row and column directions respectively.

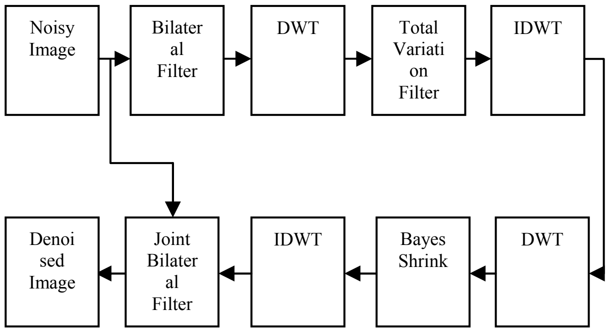
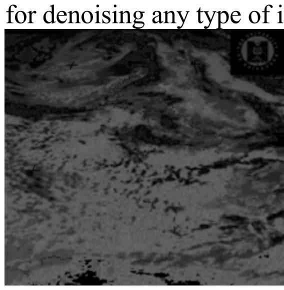


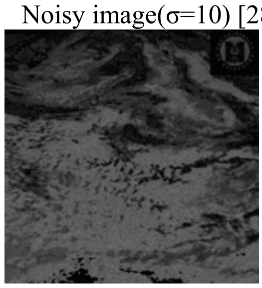
Figure 2: Proposed Method

V EXPERIMENTAL RESULTS AND DISCUSSIONS

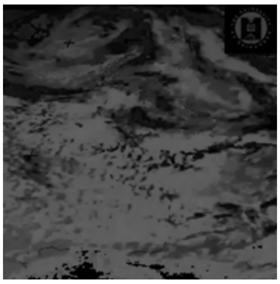
Experiments using Bilateral Filtering (BF),Wavelet Thresholding (WT), Multi Resolution Bilateral Filter (MRBF),hybrid model (B+W+B) and proposed method are conducted on a set of standard benchmark (monochrome) images such as Lena, Barbara, House, Boats, Goldhill and Peppers. Those images were added with different noises like Gaussian, Speckle, Salt and Pepper, Riccian and Random noise with standard deviations σ=10,20,30,40,50. However the results obtained with Gaussian noise added images are shown in Table I. The corresponding pictorial results are shown in Figure 3.The proposed algorithm helps to preserve the edges in the best way while suppressing the noise. The application of Joint Bilateral Filter and wavelet thresholding enhances the performance. Hence this hybrid method is recommended as a well competent and efficient model for denoising any type of images.



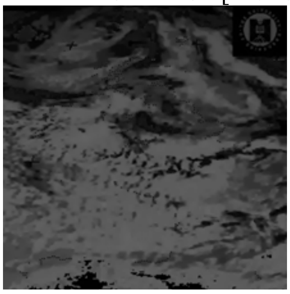
a) Noisy image(σ=10) [28.1 db]



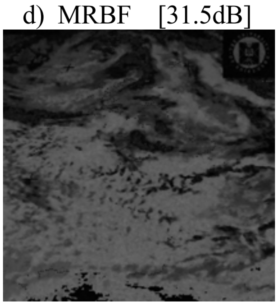
b) Wavelet Thresholding [30.5 dB]



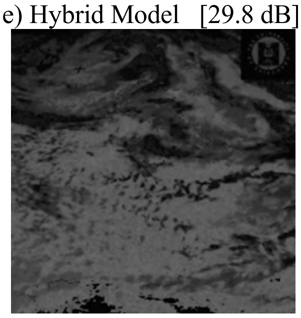
c) Bilateral Fiter [31.4 dB]



d) MRBF [31.5dB]



e) Hybrid Model [29.8 dB]



f) Proposed Method [32.1 dB]

Figure 3. Image Denoising Results on Speckle Noise added Satellite IR Image(with PSNR)

TABLE I Denoising results on Speckle Noise added images

TYPE OF FILTER	PSNR(dB)									
	σ=10	σ=20	σ=30	σ=40	σ=50	σ=10	σ=20	σ=30	σ=40	σ=50
	Lena					Satellite (IR) Image				
Noisy image	28.1	22.1	18.6	16.1	14.1	28.1	22.1	18.6	16.1	14.1
BF	33.6	29.7	27.4	25.5	23.9	31.4	27.1	25.0	23.5	22.4
WT	32.1	27.4	24.3	22.2	20.5	30.5	25.9	23.2	21.3	19.7
MRBF	33.6	30.7	29.1	27.8	26.6	31.5	27.4	25.5	24.3	23.2
B+W+B	32.5	29.8	28.4	27.4	26.6	29.8	25.7	23.6	23.1	22.8
Proposed Method	**33.7**	**30.9**	**29.6**	**28.2**	**27.0**	**32.1**	**29.6**	**26.9**	**24.6**	**24.3**
	House					**Satellite Aerial Image**				
Noisy Image	28.1	22.1	18.6	16.1	14.1	28.1	22.1	18.6	16.1	14.1
BF	35.4	31.2	28.5	26.3	24.4	32.4	28.5	26.8	25.1	23.8
WT	33.5	27.9	24.7	22.3	20.6	31.2	26.8	24.1	21.9	20.3
MRBF	36.7	33.4	31.3	29.6	28.4	31.9	28.9	27.5	26.5	25.6
B+W+B	35.7	33.3	31.5	30.2	29.1	30.4	28.1	27.1	26.5	25.9
Proposed Method	**36.9**	**33.9**	**31.9**	**30.3**	**29.3**	**32.1**	**29.4**	**27.8**	**26.7**	**26.0**

VI CONCLUSION

In this proposed work, a spatially adaptive and multiscale products wavelet thresholding image denoising framework, which incorporating both wavelet thresholding total variation and joint bilateral filtering is presented. The major factor in the performance of the proposed method is It is also observed that the application of bilateral filters on wavelet decomposed subbands in any combination with wavelet thresholding deteriorates the performance of the model, whereas, the application of bilateral filters on both before and after decomposition enhances the performance. Thus, this model is recommended as a well competent and efficient model for denoising any type of images. It may be possible to improve the results further by applying Trivariate Shrinkage Filter (TSF), Trilateral Filter and the work in this direction is under progress.

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