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Satellite Image Denoising Based on Entropy Thresholding using Shearlet Transform

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Abstract— Satellite images have become universal standard in almost all applications of image processing. However, satellite images are susceptible to noise arising due to unresolved flaws in acquisition and transmission system. Development of a denoising algorithm in satellite images is still a challenging task for many researchers. Most of the state of the art denoising schemes employ wavelet transform but the main limitation of wavelet transform is that it can preserve only point singularity. Shearlet transformation is a sparse, multiscale and multidimensional alternative to wavelet transform. Shearlet transform is optimal in representing image containing edges. In this paper, a novel image denoising algorithm utilizing shearlet transform and entropy thresholding is presented which was found to exhibit superior performance among other state of the art image denoising algorithms in terms of peak signal to noise ratio (PSNR).

Index Terms— Denoising, Discrete Shearlet Transform, Entropy Thresholding

I. INTRODUCTION

In modern era, satellite images have a plethora of applications particularly in the fields of oceanographic studies, weather forecasting, agriculture and forestry, intelligence and planning etc. The high frequency components, or the edges, present in those images constitute the vital piece of information. Unfortunately, due to the lacking image acquisition and transmission systems, the images get deteriorated with noise. So there arose an overwhelming need to develop a denoising algorithm for the elimination of noise from degraded satellite images. Researchers developed wide variety of denoising systems for satellite images. But the development of an effective denoising method keeping an eye on the preservation of fine details is still a challenging task.

Most of the conventional image denoising algorithms uses wavelet transform. Wavelet transform is effective in dealing with signals containing point singularities. Singularities such as lines or curves may or may not be present in higher dimensional signals and wavelets are unable to handle these distributed discontinuities very effectively [1]. Wavelets also have limited directional sensitivity, as a result of that edges in an image gets distorted.

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Authors in [2] introduced curvelet transform which are optimal in representing image containing edges compared to wavelets. They are implemented by using laplacian pyramid and directional filter banks. But due to the lack of multiresolution analysis, curvelets are replaced by contourlets. Authors in [3] introduced contourlet transform which can capture intrinsic geometrical features of the image compared to curvelets. But the main limitation is that they have limited directional sensitivity compared to that of curvelets. From all of the above techniques, we see that conventional image denoising algorithms distorts edges in the image due to lack of directional sensitivity and multiresolution analysis.

In [4], authors introduced shearlet transform which provides sparse representation of multi-dimensional data. They have well localized waveforms and high directional sensitivity compared to other state-of-art techniques. They are associated with multiscale and multidirectional decomposition, which enable them to capture intrinsic geometric features of image. In this paper, we had applied entropy thresholding to shearlet coefficients and output of different denoising algorithms is compared in terms of peak-signal-to-noise ratio (PSNR) in dB.

The paper is organized as follows. Section II gives an overview of Discrete Shearlet Transform and its n-term approximation error compared to conventional techniques. In Section III introduces the proposed image denoising method using entropy thresholding. Section IV gives the experimental results and comparison of different image denoising techniques. Conclusions are given in the final section.

II. THE DISCRETE SHEARLET TRANSFORM

Shearlet Transform combines multiscale and multi-directional representation and is very efficient to capture intrinsic geometric features of the multidimensional image. The shearlet decomposition of the image is shown in Figure 1. For a two dimensional image, the basis function of the shearlet transform is given by,

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$$\mathcal{A}_{DS}(\psi) = \left\{\psi_{j,k,l}(x) = |\det(D)|^{\frac{j}{2}}\, \psi(S^l D^j x - k) : j,l \in \mathbb{Z}, k \in \mathbb{Z}^2\right\} \quad (1)$$

Where $\psi \in L^2(\mathbb{R}^2)$ forms a tight frame, D and S are 2×2 invertible matrices and $|\det(B)| = 1$. Here D^j represents the dilation matrix and S^l represent the shearing matrix. From equation (1) we see that basis functions are not only limited to translation and scaling but also shearing along various orientations. As a result they provide better directional sensitivity compared to other techniques.

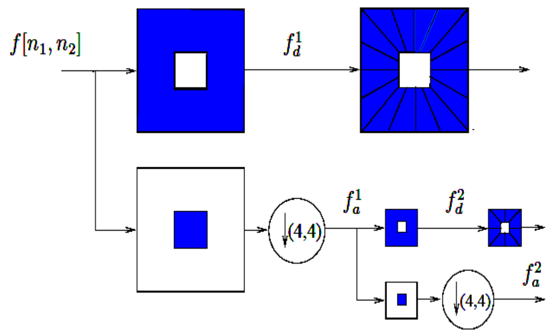

Figure 1. The shearlet decomposition of an image [4]

If $\mathcal{F} = \{\psi_{j,k,l}(x) : j,l \in \mathbb{Z}, k \in \mathbb{Z}^2\}$ represents dictionary of atoms or shearlet basis function such that every image can be represented using $\mathcal{F}$, then the approximation function is given by,

$$\mathcal{F}_N = \sum \langle \mathcal{F}, \psi_{j,k,l} \rangle \psi_{j,k,l} \quad (2)$$

The N-term approximation error which describes how well an image can be approximated by using dictionary of atoms or generally basis function is given by,

$$\mathcal{E}_N = \|\mathcal{F} - \mathcal{F}_N\| = \sum \left|\langle \mathcal{F}, \psi_{j,k,l} \rangle\right|^2 \quad (3)$$

As the value of N-term approximation decreases, we can say that algebraic sum of basis function is very close to that of original image. The N-term of approximation error of shearlet is given by,

$$\mathcal{E}_N \leq CN^{-2}(\log N)^3 \quad (4)$$

which is optimal compared to that of wavelets (CN^{-1}) and Fourier transform ($CN^{-\frac{1}{2}}$).

III. SHEARLET-BASED IMAGE DENOISING

The block diagram of the shearlet based denoising method is shown in Figure 2. The major steps involved in the denoising algorithm are explained below:

1) Initially, Gaussian noise is added to original satellite image with zero mean and variance σ^2

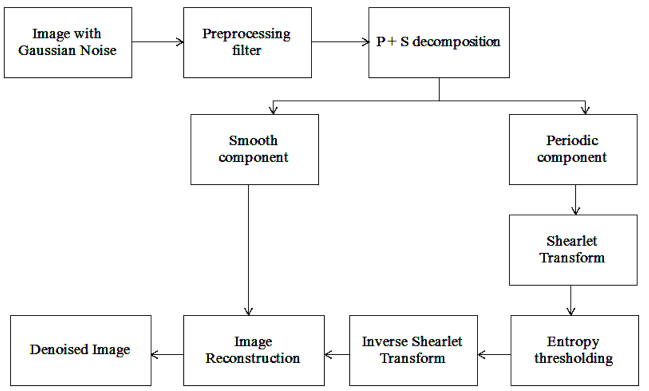

Figure 2. Block diagram of the shearlet-based satellite image denoising

2) The noisy image is applied to a preprocessing filter; median filter is used in this method
3) Image is now decomposed into periodic and smooth components; Periodic component is applied to shearlet decomposition
4) Using Discrete Shearlet Transform, decompose the periodic image into four levels and at each level of decomposition few subband images are generated
5) For each subband, compute the entropy threshold. The threshold is applied to the noisy shearlet coefficients to get denoised coefficients
6) Apply Inverse Discrete Shearlet Transform to denoised coefficients to get the denoised image.

A. *Periodic Plus Smooth Image Decomposition*

Periodic plus smooth image decomposition is used to remove discontinuities across the boundaries of an image [5]. We decompose original image (U) into periodic component (P) and smooth component (S), which is given by,

$$U = P + S \quad (5)$$

Periodic image looks similar to that of original image, but its DFT is free from edge artifacts whereas smooth component represents slow variations inside the image. Since discontinuities across border of an image causes ringing artifacts across the boundaries, the periodic plus smooth image decomposition along with shearlet transform improves quality of denoised satellite images. The steps can be summarized as:

Let input image U(q,r) be a discrete M× N image:

1) Compute the boundary image V(q,r) of the original image U(q,r)
2) Compute DFT of the boundary image, i.e., $\hat{V}(q,r)$
3) The Poisson equation is given by

$$S(q,r) = \frac{\hat{V}(q,r)}{2\cos\left(\frac{2\pi q}{M}\right) + 2\cos\left(\frac{2\pi r}{N}\right) - 4} \quad (6)$$

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4) The solution of Poisson's equation represents slow variations inside image i.e., smooth component
5) Periodic component can be obtained by subtracting smooth component from the original image

B. Shearlet Decomposition

The Figure 1 shows the shearlet decomposition of an image. The shearlet decomposition procedure is initiated by sepa- rating the periodic image into its high pass and low pass components, which is accomplished using Laplacian pyramid [6]. The high pass component is then applied to the directional filter bank, i.e., the shearing matrix. Directional filtering is not applied to the low pass component because at low frequencies could leak into the adjacent bands, which do not provide sparse representation.

C. Entropy Based Thresholding

Shearlet decomposition results in large number of shearlet coefficients and we need to separate noisy coefficients from original ones. Thresholding is very important because thresholding at large values result in loss of information whereas at low values result in background clutter. Let $S_K^j(x,y)$ represent the initial shearlet coefficient in the point (x,y) in each sub-band $K \epsilon \{K_1^j\ K_2^j \ldots K_k^j\}$ at scale j. The aim of this paper is to obtain denoised coefficient $D_k^j(\mathrm{x,y})$ at the point $S_K^j(x,y)$ by adjusting the pixel values i.e.,

$$D_k^j(\mathrm{x,y}) = \begin{cases} S_K^j(x,y) & if\ S_K^j(x,y) > T \\ 0 & if\ \ S_K^j(x,y) < T \end{cases} \quad (7)$$

where T is Entropy threshold.

The histogram of the intensity gradient in edges shows peak at low values and drops at high values. Entropy based thresholding can be applied on these type of histograms, since it computes the point at which the information content of two sides of histogram is maximum. The procedure to obtain T is summarized below [7]:

1) Compute normalized histogram
2) We divide image into two groups of pixels A and B using an initial threshold $\mathrm{T_0}$.
3) Compute Shannon entropy of A and B i.e., H(A) and H(B)
4) Optimal threshold, T= argmax [H(A)+H(B)]

IV. Results and Discussion

Four different images of resolution 512×512 pixels shown in Figure 3 are used to evaluate the performance. The experiment is implemented in MATLAB and shearlet transform can be implemented using ShearLab Software Package. Let the image is represented by 'f ' and 'w' be the zero mean additive white gaussian noise with variance σ^2.Then the noisy image can be represented as,

$$f_n = f + w \quad (9)$$

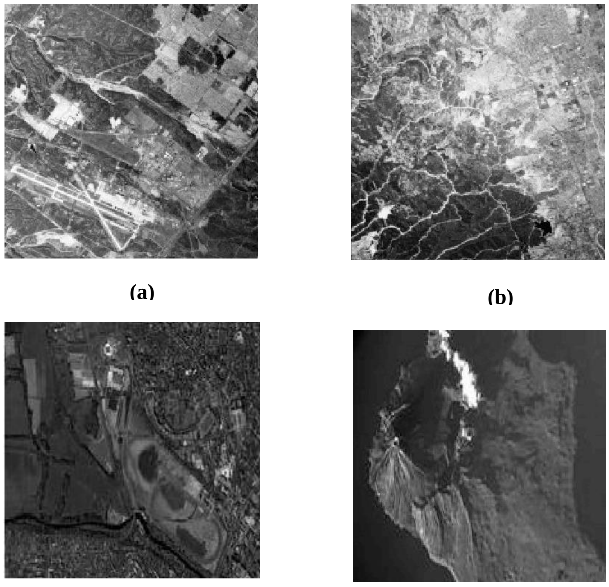
The noisy image f_n is denoised by thresholding the shearlet coefficients within each subband. The performance of the system is evaluated and compared with other algorithms using peak signal to noise ratio (PSNR) in decibels, which is given by,

$$PSNR = 20\log_{10}\left(\frac{255}{MSE}\right) \quad (10)$$

where MSE is the mean square error. Given an image $f_r(i,j)$ and original image $f_o(i,j)$, then MSE is given by,

$$MSE = \sum_{i,j} \frac{[f_o(i,j) - f_r(i,j)]^2}{M \times N} \quad (11)$$

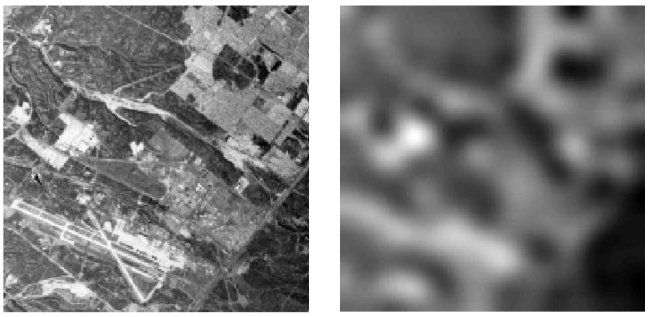
where M ×N is the size of image.



(a) (b) (c) (d)

Figure 3. Test images (a) Satellite image 1, (b) Satellite image 2, (c) Satellite image 3, (d) Satellite image 4.

In our experiment, we used a four level shearlet decomposition wherein each level consisting of 3, 3, 4 and 4 numbers of shearing directions respectively. The number of directional sub-bands within each level $N_s = 2^s$where N_s is the number of shearing directions.



(a) (b)

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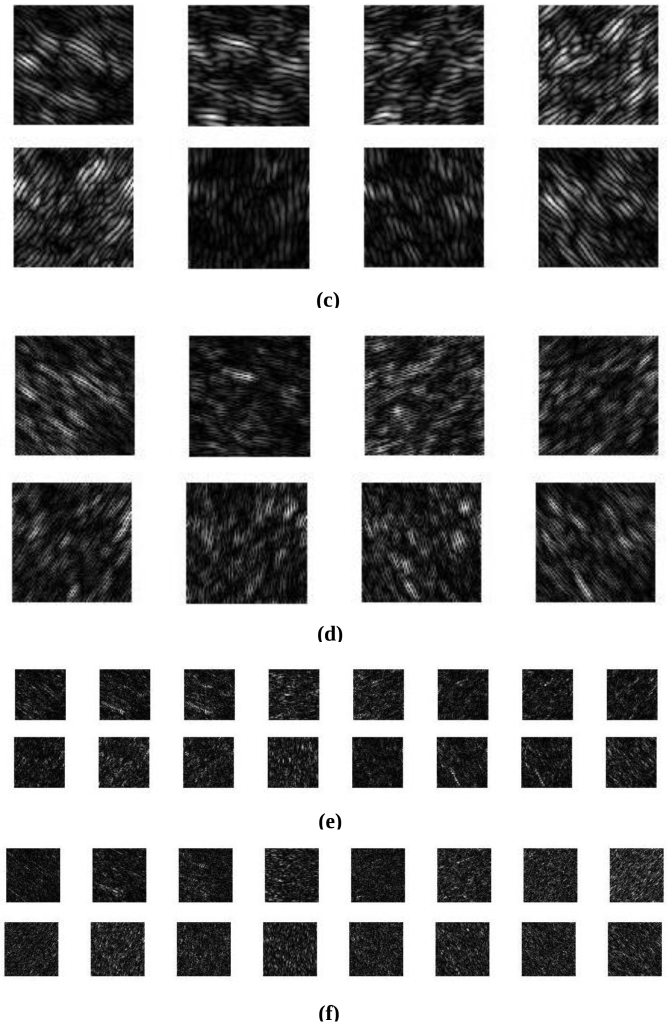

Figure 4. An illustration of shearlet decomposition (a) The original satellite image 1, (b) The approximate shearlet coefficients, (c) The detail shearlet coefficients of first level, (d) The detail shearlet coefficients of second level, (e) The detail shearlet coefficients of third level, (f) The detail shearlet coefficients of fourth level.

Thus, the number of directional subbands within each level was obtained as 8, 8, 16 and 16 respectively. The Figure 4 shows an illustration of approximation and detail coefficients of four level shearlet decomposition of satellite image 1. We tested the denoising schemes for the images having standard deviation $\sigma = 10$. The performance of proposed method compared to conventional methods is shown in TABLE I. It shows that image denoising using proposed method has high PSNR compared to other state-of-art techniques.

TABLE I
COMPARISON OF THE PERFORMANCE OF THE PROPOSED METHOD TO OTHER METHODS IN TERMS OF PSNR (dB)

Techniques /Images	**Image 1**	**Image 2**	**Image 3**	**Image 4**
Bayes Estimate	28.1022	27.1473	27.9104	26.4066
Wavelet Hard Threshold	28.2411	28.6902	28.7032	27.4145
Wavelet Soft Threshold	30.2123	29.1041	29.0718	29.9241
The Proposed Method	**32.3781**	**31.1902**	**31.2133**	**32.0453**

V. CONCLUSION

In this paper, an efficient algorithm is proposed for removing noise from corrupted image by incorporating a shearlet-based entropy thresholding. This paper shows the comparison of different denoising methods that can be applied to the shearlet transform in order to obtain denoised satellite image. The experimental result shows the proposed method provides high PSNR compared to other conventional methods. This is due to the better directional sensitivity and edge preservation ability of the shearlet transform compared to other algorithms.

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