Satellite Image Denoising Using Shearlet Transform by Optimized Entropy Thresholding

Anju T S, Nelwin Raj N R

Abstract— Satellite images are used in wide range of applications in image processing. However, satellite images are degraded due to inaccuracy of acquisition and transmission system. Development of a denoising algorithm in satellite images is still a challenging task for many researchers because there is always a trade-off between noise removal and fine edge preservation. Most of the conventional denoising algorithms uses wavelet transform but the main limitation of wavelet transform is that it can capture only limited directional information. As a result of that, it distorts edges in an image. Shearlet transformation is a new 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 optimized by using artificial bee colony optimization (ABC) is presented. The experimental results shows superior performance compared to other state-of-the art image denoising algorithms in terms of peak signal to noise ratio (PSNR).

Index Terms— Denoising, Discrete Shearlet Transform, Entropy Threshold, Artificial Bee Colony Optimization

1 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.

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.

• *Anju T S is currently pursuing M.Tech degree in electronics and communication engineering in Sree Chitra Thirunal College of Engineering, Kerala, India. E-mail: anjuts67@gmail.com*

• *Nelwin Raj N R is currently working as Assistant Professor in Sree Chitra Thirunal College of Engineering, Kerala, India. E-mail: nelwinster@gmail.com*

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 optimized using Artificial Bee Colony Optimization. Section IV gives the experimental results and comparison of different image denoising techniques. Conclusions are given in the final section.

2 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,

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

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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.

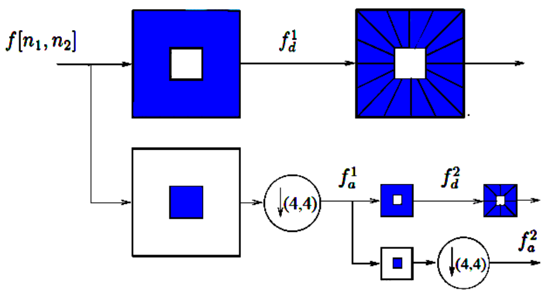

Figure 1: The shearlet decomposition of an image [4]

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,

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

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 $(CN^{-\frac{1}{2}})$.

3 The Proposed Method

The block diagram of the shearlet transform based satellite image denoising is shown in Figure 2. The main steps involved in the denoising algorithm are summarized as follows:

1) Initially, gaussian noise is added to original image with zero mean and variance σ^2
2) The noisy image is applied to a preprocessing filter; median filter is used in this method
3) Using Discrete Shearlet Transform, decompose the image into four levels and at each level of decomposition few subband images are generated
4) For each subband, compute the Entropy threshold which is optimized using artificial bee colony algorithm. The threshold is applied to the noisy shearlet coefficients to get denoised coefficients
5) Apply Inverse Discrete Shearlet Transform to modified coefficients to get the denoised image

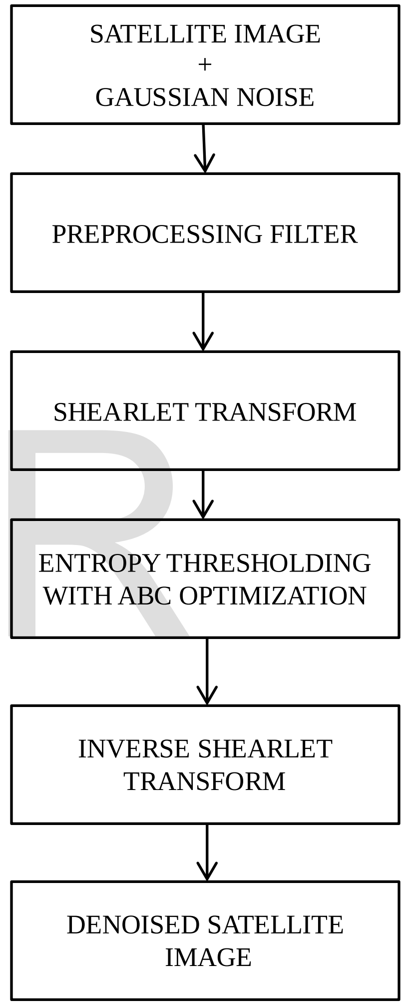

Figure 2: Block diagram of the proposed method using Entropy thresholding with ABC optimization

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 $K \in \{K_1^j\ K_2^j \ldots K_k^j\}$ at scale j. The aim of this paper is to obtain denoised coefficient $D_k^j(x, y)$ at the point $S_K^j(x, y)$ by adjusting the pixel values i.e.,

$$D_k^j(x,y) = \begin{cases} S_K^j(x,y) & if\ S_K^j(x,y) > T \\ 0 & if\ S_K^j(x,y) < T \end{cases} \quad (5)$$

where T is Entropy threshold. The major steps are detailed in the following subsections.

3.1 Entropy Thresholding

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 [5]:

1) Compute normalized histogram
2) We divide image into two groups of pixels A and B using an initial threshold 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)]

3.2 Artificial Bee Colony Optimization

ABC optimization can be used to maximize the in-between class variance of Entropy thresholding. Artificial bee colony optimization [6] is a type of optimization technique inspired from the behavior of different types of bees in its colonies. It is done by studying the information shared between three kinds of bees, namely employed bees, onlooker bees and scouts. Employed bees goes to the food source, evaluates its fitness value and search for new food source in the neighborhood whose fitness value is greater than the initial value. If the fitness value of neighborhood is greater than the initial one, employed bees forget the old value and memorize the new one. The data collected by the employed bees is shared with onlooker bees and onlooker bee selects a food source according to (8). Finally, after completing a particular number of iterations, the employed bees become scout bees and then start to search for new solutions. The fitness function is defined as:

$$fit_i = \frac{[M_G\, P_1(k) - M(k)]^2}{P_1(k)\ \times P_2(k)} \quad (6)$$

where fit_i is the variance of entropy threshold for random i. The onlooker bee selects a food source based on probability value related with fitness value provided by employed bees, i.e.,

$$P_i = \frac{fit_i}{\sum_{i=1}^{N} fit_i} \quad (7)$$

The employed bees and onlooker bees search the neighborhood sources based on,

$$V_i = X_i + r_i(X_i - X_k) \quad (8)$$

where X_i represents the original food source, k is a random positive integer in the interval [1, N] which is unique for different values of i and r_i is a random real number uniformly distributed in the interval [-1, 1].

4 Results

Satellite image of resolution 200×200 pixels shown in Figure 3 is given as input to the shearlet based denoising algorithm for evaluating the performance. The experiment is implemented in MATLAB and shearlet transform can be implemented using ShearLab Software Package.

Figure 3: Original Satellite Image

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

$$f_n = f + w \quad (10)$$

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 in terms of peak signal to noise ratio (PSNR) in decibels, which is given by,

$$PSNR = 20\log_{10}\left(\frac{255}{MSE}\right) \quad (11)$$

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,

$$MSE = \sum_{i,j} \frac{[f_o(i,j) - f_r(i,j)]^2}{M \times N} \quad (12)$$

where M ×N is the size of the satellite image.

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. Thus, the number of directional sub-bands within each level was obtained as 8,8,16 and 16 respectively as the number of directional sub-bands within each level $N_s = 2^s$ where N_s is the number of shearing directions. The Figure 4 shows an illustration of approximation and detail coefficients of shearlet transform.

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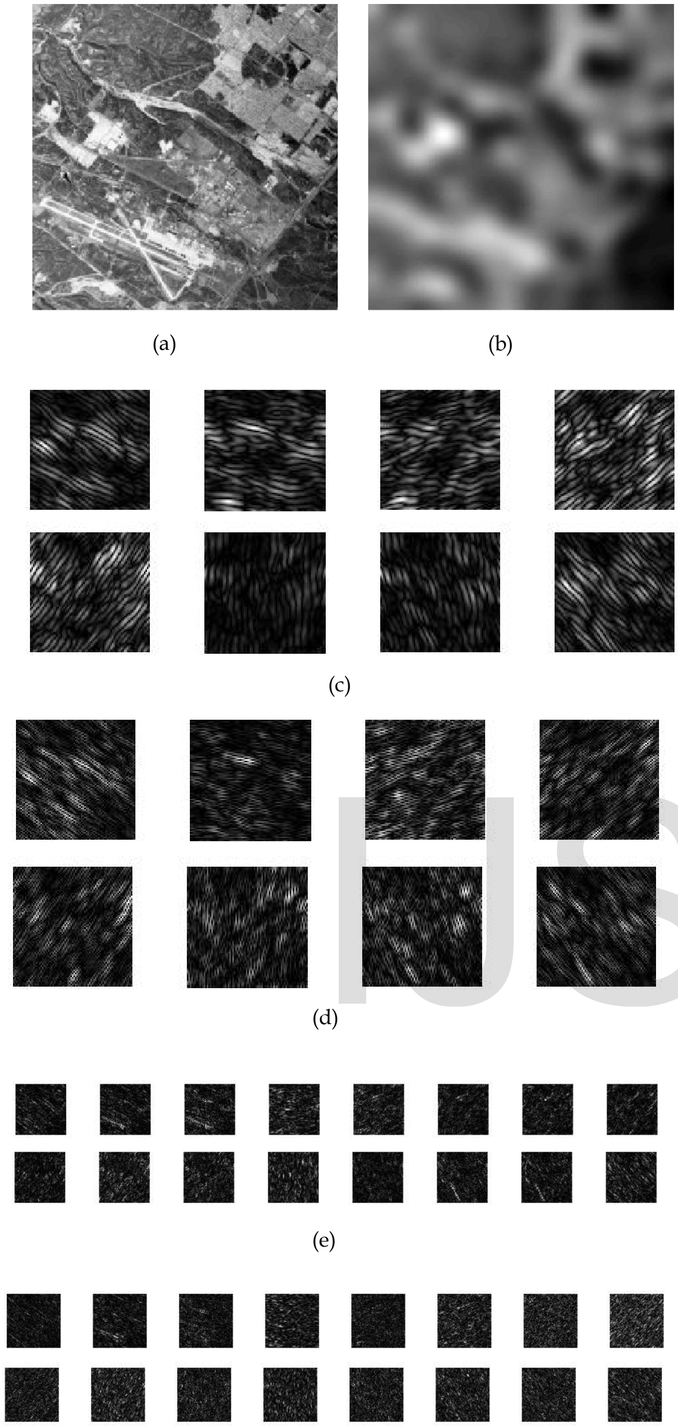

Figure 4. An illustration of shearlet decomposition (a) The original satellite image , (b) The approximate shearlet coefficients, (c) The detail shearlet coefficients of first level, (d) The detail shearlet coefficients of second level, (e) The detail shearlet coefficients of third level, (f) The detail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

We tested the denoising schemes for the images having standard deviation σ =10 to 25. 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 conventional techniques.

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

Techniques /σ	σ=10	σ=15	σ=20	σ=25
Bayes Estimate	27.4427	27.0973	26.6439	24.1391
Wavelet Hard Threshold	28.1356	24.7206	22.1067	20.1628
Wavelet Soft Threshold	28.1890	24.7601	22.1375	20.1882
The Proposed Method	30.9512	30.0074	28.2714	27.4301

5 Conclusion

In this paper, an efficient algorithm is proposed for removing noise from corrupted image by incorporating a shearlet-based entropy thresholding optimized using artificial bee colony algorithm. 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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