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CONTOURLET TRANSFORM WITH FIREFLY ALGORITHM FOR DESPECKLING OF SAR IMAGES

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ABSTRACT

Nowadays, the removal of noise in image processing is a challenge for researchers. Among all noise, speckle noise existing in satellite images, medical images and Synthetic Aperture Radar images is definitely to be removed since the details of the image are corrupted. This paper provides despeckling of Synthetic Aperture Radar (SAR) images using a new method, comprising of Contourlet transform with Firefly Algorithm (FA) to enhance the edge feature and contrast of the image. Initially, the non-linear stretch and shrink Contourlet co-efficients are applied with an improved gain function to integrate the speckle reduction with feature enhancement. Then in order to optimize the result, an evolutionary computation method such as, Firefly Algorithm is employed because of its speedy convergence. The final performance of despeckled image is compared with the combination of Contourlet transform and another optimization technique called Modified Particle Swarm Optimization (MPSO). The experimental results show that the proposed method outperforms the despeckling of image so that the texture and edge details of an image are preserved.

Keywords

SAR image, Speckle noise despeckling, Contourlet transform, Firefly Algorithm, ENL, SMPI and PSNR.

I.INTRODUCTION

The coherent processing of the scattered signal from the terrain of the earth provides the well-known noisy signal that reduces the observable details.The coherent imaging methods like

SAR imaging produce multiplicative speckle noise. To recover the sharp and clean image from the given noisy image caused due to image acquisition conditions, denoising is applied. SAR images can be used to interpret information and have many applications like bio-mass estimation, sea ice monitoring, crop estimation, flood control, oil spill monitoring and soil moisture content measurement. But a SAR image is inherently affected by speckle noise, which reduces the efficiency of the post processing steps in image processing and makes it more difficult to interpret. The main goal of despeckling process is to suppress the multiplicative noise while preserving all the scene features such as textures and edges. The speckle noise reduces the intensity level of image and tends to blur the image by reducing its fine details [1].

As the power of the signal increases the speckle noise will also increases by the same amount. Hence speckle is multiplicative noise and it can be explained with a standard deviation equal to its pixel reflectivity value. The speckle noise model can be represented in an equation (1) as,

$$f_{(i,j)} = g_{(i,j)} * n_{(i,j)} + h_{(i,j)} \qquad (1)$$

where $f_{(i,j)}$ is the measured pixel level,

$g_{(i,j)}$ is the desired pixel reflectivity,

$n_{(i,j)}$ is the multiplicative noise and

$h_{(i,j)}$ is the additive noise.

Here i, j represent the indices of the spatial location.

Since the additive noise $h_{(i,j)}$ is much less than multiplicative noise $n_{(i,j)}$, it can be removed. To fit within the display range of the envelope detected echo SAR signal is applied with logarithmic compression, which transforms the multiplicative noise into additive white Gaussian noise. This is given by,

$$\log [f_{(i,j)}] = \log [g_{(i,j)}] + \log [n_{(i,j)}] \text{ and rewritten as,}$$

$$D_{(i,j)} = X_{(i,j)} + Y_{(i,j)} \qquad (2)$$

where log [$f_{(i,j)}$] is denoted as D (i, j) and the terms log [$g_{(i,j)}$] and log [$n_{(i,j)}$] are denoted as X (i, j) and Y (i, j) respectively. Also the logarithmic conversion is used, that the additive noise can be easily removed.

About two decades, researchers developed many techniques to filter the speckle noise and retaining the image details. One method is that employs multiple look processing in frequency domain [2][3] thereby averaging statistically dependent looks on the same scene. This technique enhances the radiometric resolution at the expense of blurring. Next to this the classical spatial filters like Median filter, Lee filter [4], Kuan filter, Frost filter and other despeckling algorithms were used to do the filtering effectively with less computation complexity. In this type of filtering the image details are not effectively preserved resulting with blurred edges. Also single scale representation of a signal in time or frequency is inefficient as it is difficult to differentiate signal from noise and also these kinds of filters are not suitable for non-stationary scene signal. However it is still an unsolved problem and there is no comprehensive method that solve all the constraints taken into consideration. These limitations are overcome by using transforms based filtering of speckle noise.

Previously the concept of filtering with the use of Wavelet transform [5-7] , Curvelet Transform [8-11] and the combination of these two domains [12] were done. The Wavelet transform is a basic and powerful tool that acts on the despeckling of SAR images because of its properties of time-frequency localization, multiresolution, sparsity and decorrelation. It exhibits good performance in despeckling but during the filtering some artifacts occur and also it is not directional. Another problem in Wavelet domain is that it identifies only point discontinuities and not able to diagnose the direction of any line shaped discontinuity in the image. The extension of this is carried over by Curvelet transform [13, 14]. The Curvelet transform is used to provide optimal sparse approximations of piece wise smooth image but offers limited localization in the spatial domain because of its band limited nature. The other multi-scale analysis is experimented with Ridgelet transform [15]. The Ridgelet transform is only suited for discontinuities along straight line. For complex images where the edges were mainly along curves, the Ridgelet transform is not optimal.

The Contourlet transform with its special characteristics of multi-resolution, multidirectional and speedy operation addresses the problem of wavelet transform. The Contourlet transform includes Laplacian Pyramid [16] to capture the point of discontinuities followed by Directional Filter Banks to link the point of discontinuities into linear structure. Sparse representation for two dimensional piece wise smooth signal that resemble images is produced by Contourlet transform. Further the global search strategy, such as Firefly algorithm (FA) developed by Xin-She Yang at Cambridge University in 2007 inspired by the behavior and motion of the fireflies is applied to get the optimized result. Thus the combination of Contourlet transform with the optimization technique such as Firefly algorithm is implemented to do the despeckling of SAR images. The remainder of this paper is organized as follows: In Section II reveals about the Contourlet transform. The global search strategies, the Firefly algorithm and Particle Swarm Optimization technique are explained in Section III. The proposed method of despeckling and enhancement of SAR image based on the Contourlet with Firefly algorithm is explained in section IV. This section presents about optimization of parameters with fast convergence to integrate the speckle reduction with feature enhancement. Section V deals with the Quality evaluation metrics that decide the performance of the despeckled image and Experimental result and Analysis are focused in section VI. Section VII finally concludes the paper.

All the classical filters depend on the local statistical data related to the output denoised filter and the occurrence of the filter window over an area. Hence it is difficult to remove speckle noise without losing any data. If the filter window covers the edge of the image, the denoised output pixel value will be replaced by the statistical data from both sides of the edge of different intensity distributions.

To overcome the limitations of these spatial filters, an alternative technique has to be implemented to do the smoothing of an image with transform based operations.

2. CONTOURLET TRANSFORM

The preservation of the edges should be definitely made while despeckling of SAR images. The smoothing of SAR images can be better performed using transforms like Wavelet, Curvelet, Bandelet and Contourlet methods. In order to effectively capture image edges and contours Do and Vetterli proposed a multi-scale and multidirectional image representation method using Contourlet Transform [17, 18]. The Contourlet transform exploits smoothness of contour effectively by considering a number of directions following the contours. It is observed that the basic wavelet transform is adapted to point singularities with a problem of orientation selectivity. This major drawback is overcome by the Contourlet transform which represents the multi-scale geometric analysis.

The Contourlet transform consists of two steps which is the Laplacian Pyramid (LP) decomposition and the Directional Filter Banks (DFB) as shown in Figure (1).

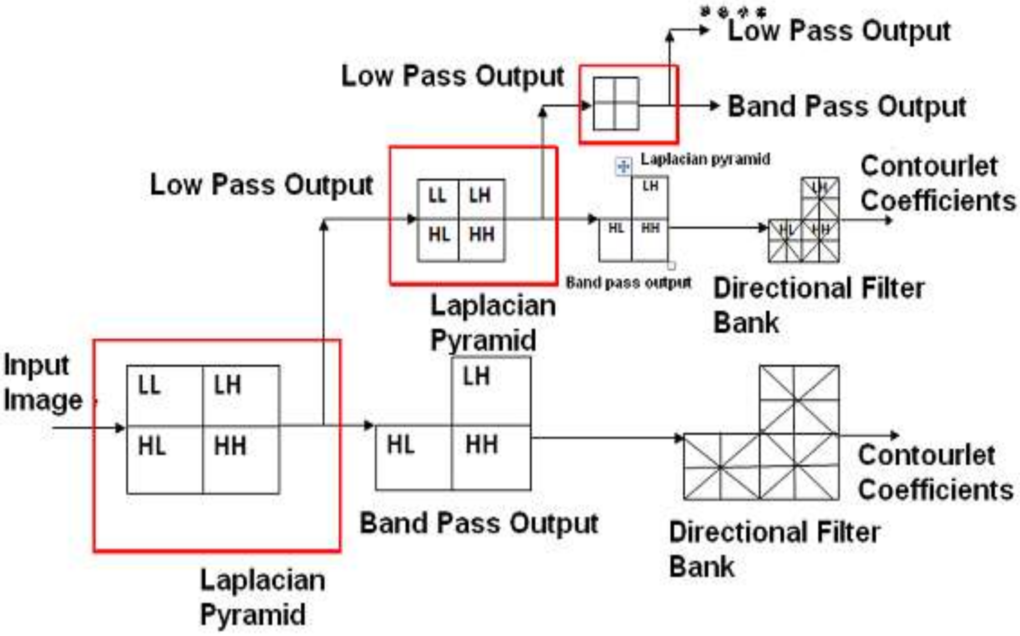

Fig. 1 Illustration of Contourlet Transform

The Figure(1) illustrates the construction of Contourlet transform by the Laplacian Pyramid(LP) [19,20,21] and the Directional Filter Banks(DFB)[22,23,24]. The input image consisting of frequency components like LL(Low Low), LH(Low High), HL(High Low) and HH(High High) is applied to LP which generates a low pass output(LL) and band pass outputs (LH,HL and HH). Then the Contourlet co-efficient are obtained by passing the pass band output to DFB [25]. To obtain more Contourlet co-efficients, the low pass output from the LP is applied to another LP till the fine details of the image are obtained. Hence the LP captures point discontinuities and DFB links point discontinuities to obtain linear structure of smooth contour.

In order to get denoised image more effectively, the thresholding approach is applied to the Contourlet co-efficients and by reconstructing, the noise reduced image with the essential characteristics is obtained.

3. OPTIMIZATION TECHNIQUES IN IMAGE ENHANCEMENT

There are various Metaheuristic Algorithms [26] developed to solve the optimization problems effectively. The parameters of Contourlet co-efficients are optimized by the evolutionary computation methods. There are two methods considered here to optimize the parameters of Contourlet co-efficients in the despeckling of SAR images say Firefly Algorithm (FA) [27] developed by Xin-She Yang at Cambridge university in 2007 and Particle Swarm Optimization (PSO) [28] which is a population based technique inspired by the social behavior of the bird flocking or fish schooling introduced by social psychologist James Kennedy and engineer Russell C.Eberhart during 1995. Here the improved version of PSO say Modified Particle Swarm Optimization technique is considered for comparison.

3.1 Firefly Algorithm (FA)

Numerous firefly species occupied in the sky produce short and rhythmic flashes in the moderate temperature region. Mostly specific species produce specific pattern. A kind of pattern formed by the attraction of male and female species depends upon many factors like the rhythm of the flashes, rate of flashing and the amount of time for which the flashes are observed. Fireflies communicate with each other only within a limited distance normally few hundred meters at night. The light is absorbed by air and becomes weaker, also the intensity of light decreases as the distance from the light source increases.

The brightness is proportional to the value of the objective function for a maximization problem. The variation in light intensity and formulation of attractiveness are the important points in Firefly algorithm since the attractiveness of a firefly is determined by its objective function.

The movement of firefly 'i' that is attracted to another more attractive (brighter) firefly 'j' is determined by,

$$\mathrm{p}_i = p_i + A_0 e^{-\gamma d_{ij}^2}\left(p_j - p_i\right) + \alpha \epsilon_i \qquad (3)$$

where, $A_o\, e^{-\gamma d_{ij}^2}(\, p_j - p_i\,)$ is due to attraction,

α is a randomization parameter and

ϵ_i is a vector of a random number uniformly distributed in [0,1].

Mostly A_0 is considered as 1 and $\propto \in_i$ [0, 1].

3.2 Particle Swarm Optimization (PSO)

The Particle Swarm Optimization (PSO) algorithm is an addition to the list of global search techniques. This is well suited for continuous variable problems and has more importance in optimization community. PSO consists of a swarm of particles and finds the optimal region in the complex search space through the interaction between the particles. PSO can be easily implemented and is computationally inexpensive in terms of both memory requirement and speed. Thus this algorithm is used in the optimization of parameters in the gain function to enhance the feature of the SAR image.

The classic PSO is as follows. If the search space is D-dimensional, the position of i^{th} particle can be represented as a D-dimensional vector $Xi = (x_{i1}, x_{i2}, x_{i3} \ldots x_{iD})$ and the velocity of the particle as $V_i = (v_{i1}, v_{i2}, v_{i3} \ldots v_{iD})$. The best previously visited position of the i^{th} particle is represented by $P_i = (p_{i1}, p_{i2}, p_{i3} \ldots p_{iD})$ and the global best position of the swarm found so far is denoted by, $P_g = (p_{g1}, p_{g2}, p_{g3} \ldots p_{gD})$. The fitness of each particle can be evaluated by putting its position into a designated objective function. The particle's velocity and its new position are updated as follows:

$$v_{id}^{t+1} = w^t v_{id}^t + c_1 r_1^t (p_{id}^t - x_{id}^t) + c_2 r_2^t (p_{gd}^t - x_{id}^t)$$

$$x_{id}^{t+1} = x_{id}^t + v_{id}^{t+1}$$

where d = {1,2,…….D}, i = {1,2,…….N}, N is the population size, the subscript t denotes the iteration number, w is an inertia weight, r_1 and r_2 are two random values in the range [0,1] and c_1 and c_2 are the cognitive and social scaling parameters which are positive constants. Some improvements are introduced to the classic PSO to avoid the premature of the swarm say Modified PSO. If the noise in image is more, the uncertainty of the image is also more. To integrate these two aspects, the evaluation criterion E_v (I) (to despeckle and enhance the given image 'I') is given by equation (4),

$$E_v(\mathrm{I}) = \frac{\exp(\eta(I)/(M\ X\ N))}{\ln(H(I))} \quad (4)$$

where, M and N are the number of pixels in the image with x and y directions.

Among these two optimization techniques the FA is potentially powerful than a favorable optimization tool [29]. Also FA includes the self-improving process and is better than PSO in terms of convergence time.

4. Proposed Methodology Of Despeckling And Enhancement Of Sar Image

The proposed despeckling and enhancement algorithms used for SAR images can be explained using the block diagram representation as shown in figure (2).

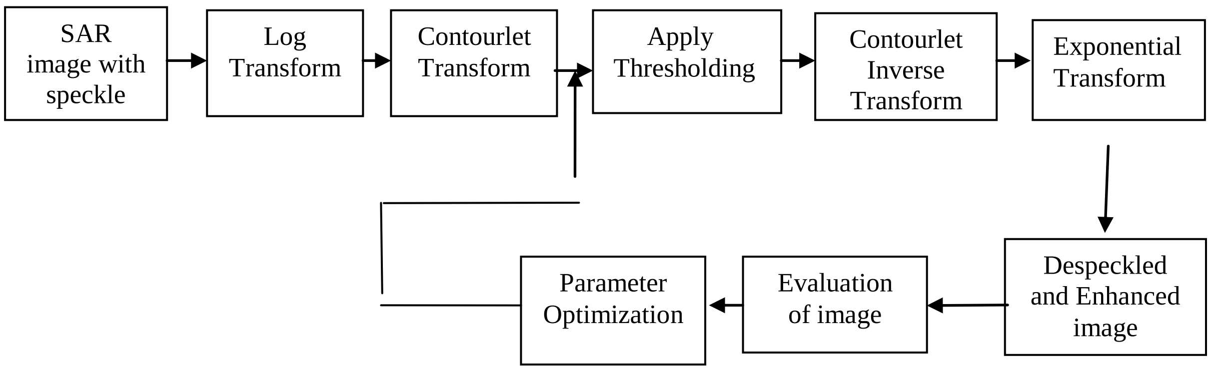

Fig. 2 Block diagram of the proposed despeckling and enhancement of SAR image.

The step by step procedure of the block diagram is explained as follows:-

- The original noisy SAR image is applied to the Logarithmic transformation block in which the multiplicative noise is converted into additive Gaussian noise as discussed in equation (2). There the original SAR image, $I_{(m,n)}$ is changed to $I'_{(m,n)}$ with removable additive noise where 'm' and 'n ' represents the row and column of the image.
- Applying Contourlet transform to $I'_{(m,n)}$ up to 'n' levels of Laplacian Pyramidal decomposition and 'm' directional decomposition at each level the Contourlet co-efficients are achieved.
- Then thresholding of Contourlet transformed image is performed. Thresholding is applied to the image to despeckle the image so that each pixel in an image is replaced if the pixel image intensity level is less than some fixed constant called threshold. If a Contourlet sub band coefficients is smaller than a predefined threshold it will be set to zero; otherwise it is kept unchanged, this function is known as hard thresholding. So it is seen that the thresholding step performs the initial act of image denoising by removing the unaccepted values less than threshold value. Here hard thresholding is applied.

- Starck et.al [30] introduced image despeckling using hard thresholding of Curvelet co-efficients and then Starck et.al [31] proposed the modified method to enhance the edges in an image with improved gain function. Here the gain function k_a is improved by modifying the Contourlet coefficients in order to enhance edges in SAR image. The gain function k_a is represented in equation (7) as,

$$k_{a(i,j)} = \begin{cases} 1 & ,if\ i < aj \\ \frac{i-aj}{aj}\left(\frac{n}{2aj}\right)^x + \frac{2aj-i}{aj} & ,if\ aj \le i < 2aj \\ \left(\frac{n}{i}\right)^x & ,if\ 2aj \le i < n \\ \left(\frac{n}{i}\right)^y & ,\ if\ i \ge n \end{cases} \tag{5}$$

where j = the noise standard deviation

x =the degree of nonlinearity

y = the dynamic range compression

a = the normalization parameter

n = is a parameter and its value under which coefficients are amplified.

The equation (7) works under two conditions that when,

i) n = sj where s is an additional parameter.

ii) n = þMc with þ < 1. Mc – Maximum Contourlet coefficient thus holds of relative band.

This foundation includes three T_1, T_2 and T_3 which meet T_1 = aj, $T_2 = 2\ T_1$, T_3 = n and $T_1 < T_2 < T_3$.

If n = sj the gain function is improved effectively but by taking ‘s’ as an additional parameter neither reduce the noise nor amplify the noise. Hence hard threshold is applied in the gain function to enhance the features of SAR image. This is done by simultaneously suppressing the speckle by modifying the gain function equation (5) to an equation (6) as,

$$k_{a(i,T)} = \begin{cases} 0 & ,if\ i < T_1 \\ \frac{i-T_1}{T_1}\left(\frac{T_3}{T_2}\right)^x + \frac{T_2-i}{T_1} & ,if\ T_1 \le i < T_2 \\ \left(\frac{T_3}{i}\right)^x & ,if\ T_2 \le i < T_3 \\ \left(\frac{T_3}{i}\right)^y & ,\ if\ i \ge T_3 \end{cases} \tag{6}$$

The main challenge in the improvement of gain function is proper selection of the parameters T_1, T_2, T_3, x & y. Hence the parameters are optimized using the global search Firefly Algorithm.

- Apply the inverse Contourlet transform on the thresholded image and then exponential transformation is carried over to obtain the despeckled image.
- The parameters for the despeckled image are computed.
- Each despeckled and enhanced image is evaluated using evaluation function.
- Repeat the steps till the stop condition of the Firefly Algorithm is satisfied.

5. QUALITY EVALUATION METRICS

This proposed algorithm has been implemented with MATLAB. The measurement of image enhancement is difficult to measure since there is no common algorithm used. Statistical measurement could be made to obtain the performance of the filter used to obtain the despeckled image. The effectiveness of applying the proposed algorithm to SAR image despecking is examined quantitatively using the Quality Evaluation metrics like, Mean Square Error (MSE), Root Mean Square Error (RMSE), Signal to Noise Ratio (SNR), Peak Signal to Noise Ratio (PSNR), Equivalent Number of Looks (ENL), Edge Save Index (ESI), Speckle Suppression Index (SSI) and Speckle Suppression and Mean Preservation Index (SMPI).

Let us consider the original image as 'G (m,n)', denoised image as 'F (m,n)' and 'N (m,n)' as noise.

5.1.1. Mean Square Error (MSE)

For any two images x and y [F and G], if one image is considered to be the noisy approximation of the other, the Mean Square Error is defined as,

$$MSE = \frac{1}{xy}\sum_{m=0}^{x-1}\sum_{n=0}^{y-1}[F(m,n) - G(m,n)]^2 \qquad (7)$$

5.1.2. Peak Signal to Noise Ratio (PSNR)

The quality of the image after despeckling is evaluated by this factor PSNR which can be defined as:

$$PSNR = 20log_{10}\left(\frac{Max_i}{\sqrt{MSE}}\right) \quad (8)$$

If Max_i^2 is considered as Maximum Intensity of noisy image and MSE is Mean Square Error then the higher quality image is obtained for higher value of PSNR.

RESULT ANALYSIS AND DISCUSSIONS

In this section, analysis of simulated results of the despeckled SAR image is presented. The despeckling procedure has been implemented using MATLAB tool and the experimental results are presented. The performance of the despeckled image is quantitatively determined by measuring all the Quality metrics of the image. Three noisy images say, the terrain of Bedfordshire, Southeast England, Horsetrack near Alburquerque and Tomakomai, Japan are taken for experimental purpose. The despeckling of these SAR images are carried over using the spatial filters like Median, Lee, Kuan and Frost filters. The despeckled image results are shown in figures 3, 4 and 5 and their Quality metrics are tabulated in Table 1.

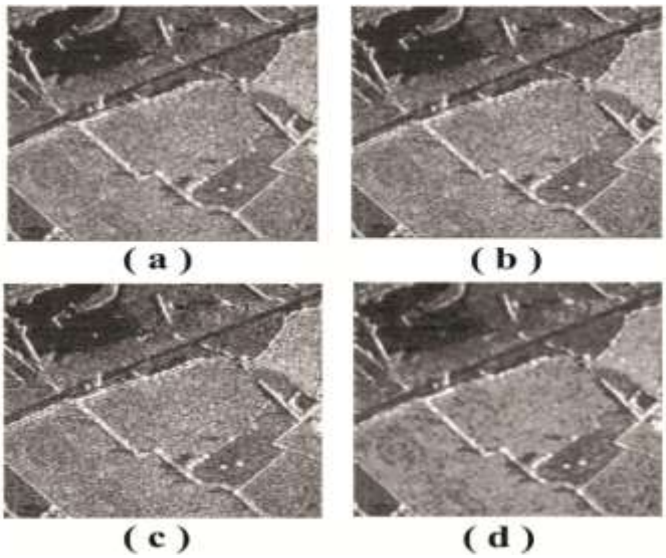

Fig 3: Despeckled Images of Bedfordshire Using (a) Median filter (b) Lee filter (c) Kuan filter (d) Frost filter

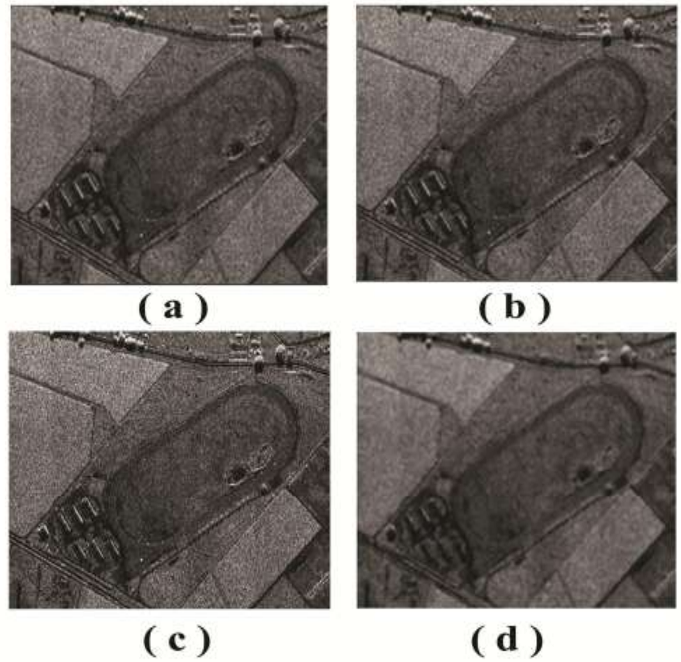

Fig 4: Despeckled Images of Horsetrack Using (a) Median filter (b) Lee filter (c) Kuan filter (d) Frost filter

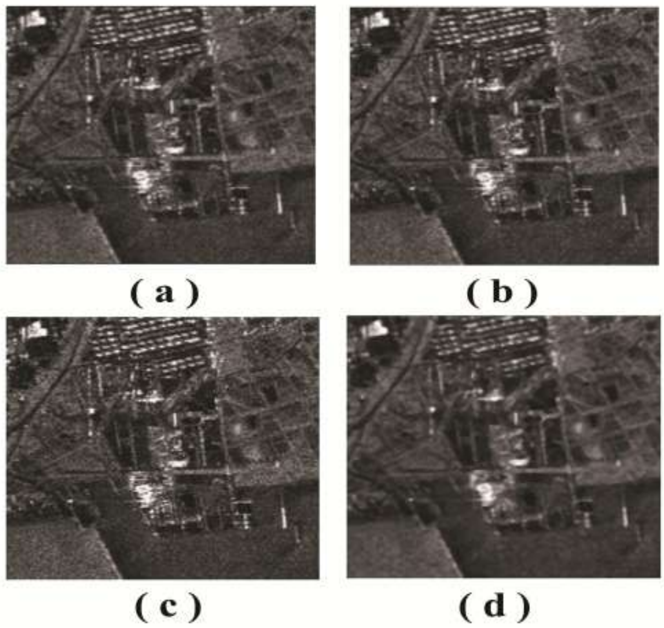

Fig 5: Despeckled Images of Tomakomai, Japan Using (a) Median filter (b) Lee filter (c) Kuan filter (d) Frost filter

Table 1: Comparison of performance metrics of different spatial filters

	Bedfordshire	Horsetrack	Tomakomai

Para- meters	Median	Lee	Kaun	Frost	Median	Lee	Kaun	Frost	Median	Lee	Kaun	Frost
MSE	0.018	0.012	0.012	0.012	0.023	0.017	0.017	0.028	0.003	0.001	0.001	0.001
ENL	6.462	6.115	6.115	3.759	9.130	8.647	8.647	5.608	5.578	4.771	4.771	4.071
SSI	0.710	0.730	0.730	0.931	0.153	0.765	0.765	0.95	0.301	0.897	8.897	0.971
SMPI	0.666	0.724	0.724	0.933	0.737	0.759	0.759	0.952	0.796	0.892	0.892	0.973
ESI_V	2.000	0.091	0.214	0.250	0.001	0.677	0.157	2.603	1.501	0.2501	2.001	3.667
ESI_H	0.281	0.469	0.174	0.302	0.002	0.467	0.621	0.167	0.601	0.583	0.762	0.714
PSNR	**20.525**	**22.17**	**22.172**	**22.318**	**19.312**	**20.609**	**20.609**	**18.578**	**28.023**	**31.857**	**31.856**	**24.695**

From the results it is observed that the PSNR values are low in spatial domain classical filters. Thus to improve the performance of despeckled image by enhancing the feature and edge details, the proposed method by the combination of contourlet transform with Firefly algorithm has been implemented. The simulated results are shown in figure 6, 7 and 8 and the Quality metrics which determines the performance of filtering using the Contourlet transform with MPSO is compared with our proposed method presented in the Table 2.

(a)

(b)

(c)

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Fig.6 Despeckling and Enhancement result of Bedfordshire SAR image. a. Original image, b. Despeckled image using Wavelet Transform with FA, c. Despeckled image using Coutourlet Transform with FA.

(a) (b) (c)

Fig.7 Despeckling and Enhancement result of Horsetrack SARimage. a. Original image, b. Despeckled image using Wavelet Transform with FA, c. Despeckled image using Coutourlet Transform with FA.

(a) (b) (c)

Fig.8 Despeckling and Enhancement result of Tomakomai SARimage. a. Original image, b. Despeckled image using Wavelet Transform with FA, c. Despeckled image using Coutourlet Transform with FA.

Table 2: Performance metrics of despeckled SAR images using Contourlet Transform with Firefly Algorithm

	Bedfordshire	**Horsetrack**	**Tomakomai**

Parameter	Contourlet Transform with MPSO	Contourlet Transform with FA	Contourlet Transform with MPSO	Contourlet Transform with FA	Contourlet Transform with MPSO	Contourlet Transform with FA
MSE	0.000104	0.0012	0.000156	0.0008	0.00134	0.0004
ENL	16.7895	4.4170	30.0964	3.9763	16.692	3.5460
SSI	0.9372	0.9964	0.5627	0.9970	0.6862	1.0035
SMPI	0.9861	0.9945	0.5638	0.9964	0.6796	1.0033
ESI-H	0.8065	0.7844	0.0309	1.0946	0.2002	1.2828
ESI-V	1.0342	0.6856	0.5728	0.8246	0.0732	0.8641
PSNR	**64.3008**	**77.2420**	**65.1984**	**78.9093**	**64.4352**	**81.4666**

The results of proposed method is compared with results of the previous algorithm, despeckling of SAR image using Contourlet Transform with Modified Particle Swarm Optimization.

From the table 2, it is observed that after simulation, the combination of Contourlet transform with Firefly Algorithm produces much improved Peak Signal to Noise Ratio (PSNR). It is also seen that, on comparison the Edge Save Index on both horizontal and vertical directions are higher in the proposed technique than Contourlet transform with Modified Particle Swarm Optimization. From the parametric results it is evident that the proposed method produces more efficient despeckled SAR image with enhanced feature and edge details.

7.CONCLUSION

In this paper, an adaptive method of speckle reduction and feature enhancement for SAR images based on Contourlet transform with Firefly algorithm have been proposed. An improved Quality metrics of the image is developed to integrate the speckle reduction with feature enhancement, by nonlinearly shrinking and stretching the co-efficients of Contourlet transform and optimized the parameters using Firefly Algorithm. The Firefly algorithm is applied to make the speedy convergence and avoid premature convergence in optimizing the parameters. The result of the proposed method is compared with the previous technique, the despeckling using Contoulet transform with Modified Particle Swarm Optimization. After the analysis, it is concluded that the simulated and real SAR images were despeckled and their features were enhanced which provide excellent performance of despeckling with our proposed method. This is computationally expensive due to iterative operation of Firefly Algorithm and improved version may be adopted by parallel operation which will reduce the computation time effectively and can be taken as future work.

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