Despeckling of SAR Images via an Improved Anisotropic Diffusion Algorithm

Anurag Gupta, Anubhav Tripathi, and Vikrant Bhateja

Deptt. of Electronics and Communication Engineering,
Shri Ramswaroop Memorial Group of Professional Colleges,
Faizabad Road, Lucknow-227105, (U.P.), India
{anuraggpt8,proabhi9,bhateja.vikrant}@gmail.com

Abstract. Synthetic Aperture Radar (SAR) is a powerful tool for producing high-resolution images but these images are highly contaminated with speckle noise. This paper proposes an improved Anisotropic Diffusion Algorithm for despeckling SAR images. The proposed algorithm is obtained by using a diffusion coefficient which consists of a combination of first and second order derivative operators. The spatial variation of this diffusion coefficient occurs in such a way that it prefers forward diffusion to backward diffusion resulting in improved structural details and edge preservation. The simulation results also show better computational efficiency in comparison to other denoising techniques.

Keywords: Speckle, SAR images, Diffusion coefficient, Multiplicative noise.

1 Introduction

Speckle is a kind of multiplicative noise that affects most of the coherent imaging systems. The presence of speckle noise in an imaging system reduces its resolution; especially for low contrast images such as Synthetic Aperture Radar (SAR) images. This creates problem in automatic processing of SAR images, used in various applications like crop monitoring, search and rescue operations, military target detection etc. Therefore, the suppression of speckle noise is an important consideration in the design of coherent imaging systems. Over the last few years, various despeckling techniques for SAR images have been proposed [1-3]. Among them, Anisotropic Diffusion (AD) filters [4] based on nonlinear heat diffusion equation surpass most others in terms of accuracy and robustness. These filters fall into the category of Partial Differential Equation (PDE) based image processing, originated from the work of Perona and Malik [5]. This method was capable of reducing the noise content of the image as well as enhancement of the boundary information within the data. However, this filter [5] introduced *blocky effects* and it blurs the edges with the number of iterations of the filter. Yu and Acton, therefore introduced an edge sensitive diffusion method, called Speckle Reducing Anisotropic Diffusion (SRAD) filter [6], which defined an instantaneous coefficient of variation to detect the edges in the noisy images. Aja-Fernández and Alberola-López [7] further developed this method by introducing a new AD filter,

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known as Detail Preserving Anisotropic Diffusion (DPAD) filter. Although, both the DPAD and SRAD methods enhanced the prominent edges during speckle filtering; they also resulted in blurring, thereby eradicating detailed features of the image. To enhance flow-like patterns, Weickert [8] developed Coherent Enhancing Diffusion (CED) filter in which the concept of structure tensor was introduced, which allowed the smoothing level to vary directionally. This concept was further utilized in Nonlinear Coherent Diffusion (NCD) technique [9] which implemented diffusion by discriminating between different levels of speckle and filtering only those regions which closely resembled an optimum level of speckle. Although, NCD yields high computational speed, robust parameter selection and texture preservation characteristics but it also introduced certain artifacts in the images. To overcome this drawback, Krissian [10] introduced Oriented Speckle Reducing Anisotropic Diffusion (OSRAD) filter which combined the matrix diffusion scheme and DPAD filter, for reducing speckle as well as preserving and enhancing the contours. But, the usage of diffusion matrix scheme requires heavy computational requirements [11]. Therefore, the present work proposes a novel AD algorithm incorporating a diffusion coefficient based on first and second order derivative operators. The proposed algorithm leads to efficient speckle suppression in homogeneous areas, thereby preserving edges and detailed features as well as lowering the unnecessary computational overhead. Peak Signal-to-Noise Ratio (*PSNR*), and Speckle Suppression Index (*SSI*) are used as quality parameters to evaluate the performance of proposed algorithm. The rest of the paper is organized as follows: Section 2 describes the proposed methodology; the quality parameters used for performance evaluation, experimental procedures and result analysis are explained under Section 3. Based on the analysis of obtained results, Section 4 draws the conclusion.

2 Proposed Methodology

2.1 Background

The AD filters use PDE based methods [13] to resolve an image in order to get expected results by removing the noise. The idea of using PDE based noise removal techniques can be explained as follows:-

Consider an image f_o contaminated with speckle noise ($\chi_{speckle}$) resulting in a noisy image f_n, such that:

$$f_n = f_o \cdot \chi_{speckle} \tag{1}$$

In order to regularize f_n, the variations posed by speckle $\chi_{speckle}$ has to be minimized which can be estimated by gradient norm of image:

$$\left\|\nabla f_n\right\| = \sqrt{{f_{n_i}}^2 + {f_{n_j}}^2} \tag{2}$$

where: $\left\|\nabla f_n\right\|$ represents gradient norm of the noisy image. The variational problem of (2) is the minimization of the energy function, $E(f_n)$ as:

$$\min_{f_n:\Omega\to R} E(f_n) = \int \left\|\nabla f_n\right\|^2 d\Omega \tag{3}$$

The necessary condition for minimizing $E(f_n)$ is given by Euler Lagrange equation:

$$\frac{\partial f}{\partial t} = c\nabla^2 f \tag{4}$$

Here, (4) is known as heat equation with the initial condition, $f = f_n$ at t = 0 and diffusion coefficient *c*. This equation can also be stated as:

$$\frac{\partial f}{\partial t} = div\left(c.\nabla f\right) \tag{5}$$

In terms of Continuity equation, the diffusion process can also be expressed as:

$$\frac{\partial f}{\partial t} = -div\left(J\right) \tag{6}$$

where: $J = -c.\nabla f$ is a flux created by concentration gradient ∇f and aims to overcome the gradient ∇f . Thus, the PDEs (5) and (6) for diffusion process can be classified on the basis of diffusion coefficient *c* in the two categories viz. Isotropic Diffusion equations, when *c* is a constant and Anisotropic Diffusion equations, when *c* is a function of gradient of image, i.e.

$$c = g\left(\| \nabla f \|\right) \tag{7}$$

Anisotropic Diffusion equations provide backward diffusion around transients and forward diffusion in smooth areas in favor of edge sharpening and noise removal [14].

2.2 Proposed Diffusion Coefficient

Perona & Malik replaced the classical isotropic diffusion (5), by introducing the concept of gradient in diffusion constant as shown in (7). By concept the Gradient operator serves to be an effective operator for detecting sharp edges as gradient of a scalar field is a vector field that points in the direction of greatest rate of increase of scalar field [5]. However, if the edges are not sharp i.e. pixel gray level do not change rapidly over space, then it produces very wide and blurred edges. In such cases, a laplacian operator proves to be more effective in comparison to a gradient operator. Laplacian is a second order derivative operator which has a zero crossing level in the middle of edges. Therefore, it can detect the edges more efficiently even when the edges are weak, by detecting the zero crossing level in the image [15]. Hence, a new diffusion coefficient with the combination of first order derivative (gradient) and second order derivative (laplacian) operators can be formulated as:-

$$c = g\left(\| \Delta f \|\right) \tag{8}$$

$$c = \left(\frac{1 + \| \Delta f \|}{1 + \| \nabla f \|}\right)^2 \tag{9}$$

where: Δ denotes laplacian operator and ∇ denotes gradient operator. The value of *c* evaluates to a real number ranging between 0 to 1.

2.3 Proposed Despeckling Algorithm

The algorithm proposed in this work is initiated by applying the solution of PDE mentioned in (5) to the noisy SAR images through several iterations until the diffusion gets saturated. Firstly, the gradient and laplacian operators are applied to the noisy input image (initialized as f^0 (x , y)) in order to calculate the proposed diffusion coefficient given by (9). Next, a 3x3 spatial mask centered at any pixel location f (i, j) is taken to calculate the directional derivatives of the central pixel in respective directions. This can be mathematically expressed as under:

$$\left.\begin{aligned}
\nabla_N f^n_{i,j} &= f^n_{i-1,j} - f^n_{i-1,j} \\
\nabla_{NE} f^n_{i,j} &= f^n_{i-1,j+1} - f^n_{i,j} \\
\nabla_{NW} f^n_{i,j} &= f^n_{i-1,j+1} - f^n_{i,j} \\
\nabla_E f^n_{i,j} &= f^n_{i,j+1} - f^n_{i,j} \\
\nabla_W f^n_{i,j} &= f^n_{i,j-1} - f^n_{i,j} \\
\nabla_{SE} f^n_{i,j} &= f^n_{i+1,j-1} - f^n_{i,j} \\
\nabla_{SW} f^n_{i,j} &= f^n_{i+1,j+1} - f^n_{i,j} \\
\nabla_S f^n_{i,j} &= f^n_{i+1,j} - f^n_{i,j}
\end{aligned}\right\} \tag{10}$$

where: n denotes n-th iteration and ∇_N denotes directional derivative in north direction. Similarily N, S, E, W, NE, NW, SE, SW mentioned as subscript with ∇_N denotes directional derivative in north, south, east, west, north-east, north-west, south-east, south-west directions respectively. Then, a simple numerical scheme [5] is used to discretize the solution of (5) which can be stated as:

$$f^{n+1}_{i,j} = f^n_{i,j} + \lambda \begin{bmatrix} c_N.\nabla_N f^n_{i,j} + c_{NE}.\nabla_{NE} f^n_{i,j} + c_{NW}.\nabla_{NW} f^n_{i,j} + c_E.\nabla_E f^n_{i,j} + c_W.\nabla_W f^n_{i,j} + \\ c_{SW}.\nabla_{SW} f^n_{i,j} + c_{SE}.\nabla_{SE} f^n_{i,j} + c_S.\nabla_S f^n_{i,j} \end{bmatrix} \tag{11}$$

where: $\lambda \in [0,1/4]$ and c_N is the diffusion coefficient for the North direction. Similarily, c_X denotes the diffusion coefficient in the respective X direction. This discrete version of the solution, when applied to the image results in a despeckled image (f^1 (x, y)) which is then compared with the original noisy image $f^0 (x, y)$ and the resultant error is denoted as E_1:

$$E_1 = | f^1 (x, y) - f^0 (x, y) | \tag{12}$$

Then, the image $f^0 (x, y)$ at the input is replaced by the resulting image, $f^1 (x, y)$ and the entire process is repeated again such that the error computed is denoted as E_2. The difference between E_1 and E_2 is therefore:

$$\Delta E = E_1 - E_2 \tag{13}$$

Where: ΔE serves to define the stopping criterion. If $\Delta E \geq 0$, then the process is terminated else $f^1 (x, y)$ is again replaced by the processed image $f^2 (x, y)$ and E_2 is stored in E_1 and the whole process is repeated until the error remains less than zero. In this way, the final image produced through several number of iterations is treated as the despeckled image.

3 Results and Discussion

3.1 Evaluation of Proposed Algorithm

Peak Signal-to-Noise Ratio (*PSNR*)

It is generally pre-assumed that higher the value of *PSNR* [12] better is the quality of restored image and is mathematically given as:

$$PSNR(dB) = 10\log_{10}\frac{(2^r - 1)}{MSE} \tag{14}$$

where: r is the number of bits and *MSE* is the Mean Squared Error. The term *MSE* is formulated as:

$$MSE = \frac{1}{MN}\sum_{i-1}^{M}\sum_{j-1}^{N}[f(i,j) - y(i,j)]^2 \tag{15}$$

where: $f(i\ ,\ j)$ denotes the original image, $y(i,\ j)$ denotes the despeckled image, i and j are the pixel position of the M x N image. The advantage of using *PSNR* is its calculative simplicity and good mathematical convenience in terms of optimization.

Speckle Suppression Index (*SSI*)

It is an average measure of the amount of speckle present in the despeckled image as a whole when compared to the noisy image. So, the lower value of *SSI* signifies the better quality of the image. It is related to the ratio of the local deviation in pixel brightness to the mean pixel brightness averaged over the entire image. *SSI* is mathematically defined as:

$$SSI = \frac{1}{MN}\sum_{i-1}^{M}\sum_{j-1}^{N}\frac{\sigma(i,j)}{\mu(i,j)} \tag{16}$$

where: $\sigma(i,j)$ is the local deviation of the image pixels and $\mu(i,j)$ is the corresponding mean of the entire image. *SSI* is calculated for both noised and denoised image.

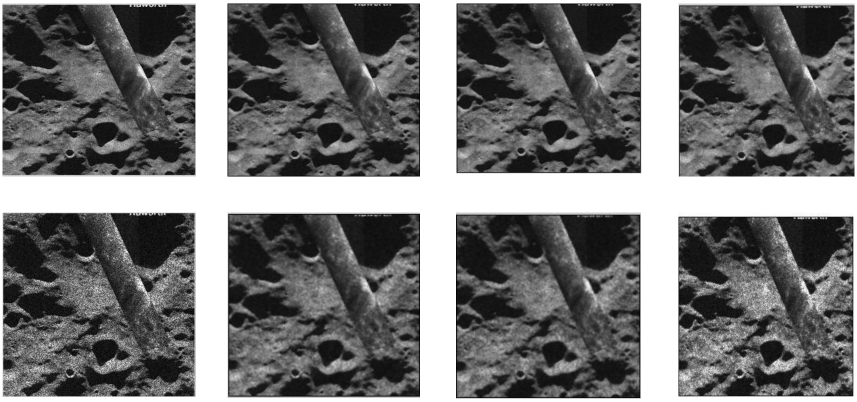
3.2 Experimental Procedures and Results

SAR input images (Crater) of size 256x256 is initially normalized to scale down the pixel intensity between the range 0 to 1. Speckle noise of varying intensities (ranging between $\sigma = 0.001$ to 0.1) is superimposed on the normalized SAR images to produce the noisy image. With the help of (9), the diffusion coefficient is calculated and is further used in diffusion process as discussed in section 2. The quality of the processed image is checked with the help of *PSNR* and *SSI* quality metrics where *PSNR* is used to calculate ΔE and thus, decides the stopping criterion. Therefore, the number of iterations required to achieve an optimum despeckling result depends on the value of *PSNR* of image at each iteration.

Fig. 2 shows the simulated results for Anisotropic Diffusion Algorithm of SRAD and DPAD along with those obtained by using proposed algorithm at various intensity levels of speckle noise. The speckle noise is significantly removed in the images obtained by using the proposed Anisotropic Diffusion Algorithm with minimum iteration [11]. The results are more reliable in terms of edge preservation and reduced speckle noise. Moreover, even at higher value of noise intensity such as 0.1 the results are quite relevant in comparison with those obtained from SRAD and DPAD.

(I)

(II)



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

Fig. 1. (a) Original Image (Crater): **(I)** 0.01 speckle noise **(II)** 0.1 speckle noise. Despeckled SAR image by: **(b)** SRAD **(c)** DPAD **(d)** Proposed AD Algorithm.

3.3 Analysis

The analysis of AD filters is done on the basis of simulation results and corresponding values of *PSNR* and *SSI* obtained for a SAR image (crater). As discussed earlier, the *PSNR* values are required for quality assessment of restored images while *SSI* values measure the relative amount of speckle present in the denoised image when compared with the noisy image. Taking this under consideration, the results regarding to the values of *PSNR* and *SSI* are tabulated for DPAD, SRAD and for proposed AD algorithm at various speckle noise levels ranging from 0.001 to 0.1. The *PSNR* values for DPAD and SRAD in table 1 are high at low level noise and are decreasing with increase in noise level. The subsequent analysis of *PSNR* values for the proposed algorithm show high values at various noise levels and thus, the quality of images obtained through this algorithm can be considered to be better than the others. Similarly, the *SSI* values in table 2 are required to be as low as possible. The relative deviation in values for noisy and denoised SAR images for the proposed AD algorithm is very high in comparison with others, revealing the fact that the denoised image contains less amount of speckle noise. Therefore, this algorithm is efficient in preserving the edge details and despeckling the images while the earlier proposed filters like SRAD and DPAD exhibited these properties but with certain short comings of blurred edges and less filtered noise content. Moreover, the proposed algorithm also results in fast convergence of the filtering process as only 1 iteration is required to despeckle the noisy image having speckle intensity up to 0.1. However, for speckle intensity greater than 0.1, number of iterations required increases to 2 which is still much less that required for DPAD and SRAD filter (around 5-6 number of iterations).

Table 1. PSNR(dB) values for different AD Filters calculated for the SAR image

Noise Level (variance)	DPAD	SRAD	Proposed AD Algorithm
0.001	26.3596	26.4449	28.5470
0.01	25.7691	25.8422	27.8240
0.02	25.2080	25.2636	27.8141
0.04	24.5640	24.7008	25.9425
0.1	23.5550	23.7880	25.0727

Table 2. SSI values for different AD Filters calculated for the SAR image

Noise level (variance)	DPAD		SRAD		Proposed AD Algorithm	
	Noisy Image	Denoised Image	Noisy Image	Denoised Image	Noisy Image	Denoised Image
0.001	0.2023	0.1562	0.2023	0.1549	0.2023	0.1546
0.01	0.2299	0.1700	0.2299	0.1699	0.2299	0.1667
0.02	0.2548	0.1805	0.2548	0.1779	0.2548	0.1780
0.04	0.2970	0.1931	0.2970	0.1930	0.2970	0.1829
0.1	0.3926	0.1969	0.3926	0.1956	0.3926	0.1948

4 Conclusion

In this paper, an improved algorithm for AD filters is proposed along with a new coefficient of diffusion. The evaluation of proposed algorithm on the basis of quality metrics such as *PSNR* and *SSI* exhibits its relative dominance over other techniques in terms of preserving the edge details and despeckling of SAR images. Also, the requirement of less number of iterations for despeckling process proves the simplicity and effectiveness of the proposed diffusion coefficient in comparison to the other more complex methods like SRAD and DPAD.

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