DESPECKLING OF SAR IMAGES USING RECURSIVE FILTER BASED, MODEL BASED AND ANISOTROPIC DIFFUSION BASED METHODS

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ABSTRACT: *Synthetic aperture radar (SAR) generates images that are severely degraded by a type of multiplicative noise known as speckle. Speckle is caused by random interference of the backscattered electromagnetic waves due to the roughness of the imaged surface. Since speckle generally tends to obscure image details, reduction of the speckle noise is important in most detection and recognition systems where speckle is present.*

In this paper three despeckling methods namely Recursive filter based despeckling, Model based despeckling and Anisotropic diffusion for despeckling are compared. The MATLAB software has been used for the above mentioned methods. The performances are evaluated in terms of statistical parameters like Mean, Standard deviation, Root Mean Square Error (RMSE) and Peak Signal to Noise Ratio (PSNR). These parameters are used to calculate the quality of the output image obtained from the above mentioned despeckling methods. Based on the values of these parameters the performance of the methods in terms of speckle removal is discussed.

KEYWORDS: *Synthetic aperture radar, Multiplicative noise, Speckle, Despeckling, Recursive filter, Model based, Anisotropic diffusion, Performance.*

1. INTRODUCTION

A synthetic aperture radar (SAR) is used to obtain high resolution images of the earth. SAR is a radar technique in which a physically large antenna is simulated by gathering data while airborne radar is flying over the target. The distance travelled by the antenna is the synthetic aperture. This simulates an antenna whose length is physically difficult to carry in an airplane [She95].

SAR is used in many applications including mineral exploration, oil spill studies, forestry, floods monitoring, hurricanes and earthquakes, agricultural monitoring, oceanography, and geology. It is also used for reconnaissance, surveillance, and targeting in military applications since it provides images in any weather or light conditions [Doe96, Leb90].

2. SPECKLE NOISE

This noise is multiplicative in nature, so simple filtering will not remove it [Leb90]. The speckle noise model may be approximated as multiplicative [Jai89] and is given by

$$I(i, j) = R(i, j)\, u(i, j) + \alpha(i, j) \quad (1)$$

where I(i, j) is the noisy image and R (i, j) denotes the intensity of the image without speckle, u (i, j) and α (i, j) are the multiplicative and additive components of the speckle noise respectively. When applied to SAR images, only the multiplicative component u of the noise is considered, hence the above equation can be considerably simplified by disregarding the additive noise term. This leads to the following simplified model:

$$I(t) = R(t)\, u(t) \quad (2)$$

where t = (i, j) is the spatial coordinates of the current pixel.

2.1 Speckle Noise Reduction

Speckle noise degrades the appearance and quality of SAR images. Ultimately it reduces the performances of important techniques of image processing such as detection, segmentation, enhancement and classification etc. That is why speckle noise should be removed before applying

any image processing techniques [AJK07]. Although the existing despeckle filters are termed as "edge preserving" and "feature preserving", there exist major limitations of the filtering approach.
1) The filters are sensitive to the size and shape of the filter window.
2) The existing filters do not enhance edges, they only inhibit smoothing near edges.
3) The despeckle filters are not directional.

3. OBJECTIVE OF THE PAPER:

1. To reduce the speckle by using algorithms such as Model Based Despeckling, Anisotropic Difusion for speckle reduction and Recursive Despeckle Filtering.
2. To test the algorithms with real and simulated speckle SAR images and compare their performances in terms of Mean, Standard deviation, RMSE and PSNR.

4. LITERATURE REVIEW

Scott T. Acton, "Deconvolutional Speckle Reducing Anisotropic Diffusion", [Act05] proposed a new Partial differential equation (PDE) that combines the enhancement of speckle reducing anisotropic diffusion (SRAD) with the mechanism of deconvolution. The method surpasses the edge localization ability of SRAD while yielding lower error in terms of area estimation and improved detection of fine features. Alin Achim, Ercan E. Kuruoglu and Josiane Zerubia, in "SAR Image Filtering Based on the Heavy-Tailed Rayleigh Model", [AKZ06] proposed a novel adaptive despeckling filter and derived a maximum a posteriori (MAP) estimator for the radar cross section (RCS). A logarithmic transformation was employed to change the multiplicative speckle into additive noise. Hye Suk Kim, Keon Hee Park, Hyo Sun Yoon and Guee Sang Lee, "Speckle Reducing Anisotropic Diffusion based on Directions of Gradient", [K+08] proposed a new anisotropic diffusion method based on directions of gradient. As a result, when the magnitude of gradient is large enough, the pixel is considered as the edge. Jarabo-Amores.P, Rosa-Zurera.M, Mata-Moya.D, Vicen-Bueno.R, "Mean-Shift Filtering to Reduce Speckle Noise in SAR Images", [J+09] proposed a filtering technique based on the algorithm "Mean Shift", to reduce the speckle noise in SAR images, preserving their quality by maintaining textures, sharp edges and shapes. Daniela Espinoza Molina, Dusan Gleich, and Mihai Datcu, in "Gibbs Random Field Models for Model-Based Despeckling of SAR Images", [MGD10] made a comparison between three different despeckling methods based on a Bayesian approach and Gibbs random fields. The used methods are Gauss–Markov random field (GMRF) and autobinomial modeling, which operate in the image domain, and the GMRF approach, which operates in the wavelet domain.

5. RECURSIVE FILTER

Recursive filters are an efficient way of achieving a long impulse response, without having to perform a long convolution. They execute very rapidly, but have less performance and flexibility than other digital filters. Recursive filters are also called Infinite Impulse Response (IIR) filters, since their impulse responses are composed of decaying exponentials. This distinguishes them from digital filters carried out by convolution, called Finite Impulse Response (FIR) filters.

5.1 Flow Diagram of Recursive Filter

This diagram is presented in figure 1.

5.2 Explanation of the Block Diagram

5.2.1 Texture Filtering

Texture filtering is a cheap approximation to anti-aliasing. Spatial anti-aliasing is the technique of minimizing the distortion artifacts known as aliasing when representing a high-resolution image at a lower resolution.

5.2.2 Bilinear Filtering

Bilinear filtering is a texture filtering method used to smooth textures when displayed larger or smaller than they actually are. Most of the time, when drawing a textured shape on the screen, the texture is not displayed exactly as it is stored, without any distortion.
Because of this, most pixels will end up needing to use a point on the texture that's 'between' texels, assuming the texels are points in the middle (or on the upper left corner, or anywhere else) of their respective 'cells'. Bilinear filtering uses these points to perform bilinear interpolation between the four texels nearest to the point that the pixel represents (in the middle or upper left of the pixel, usually).

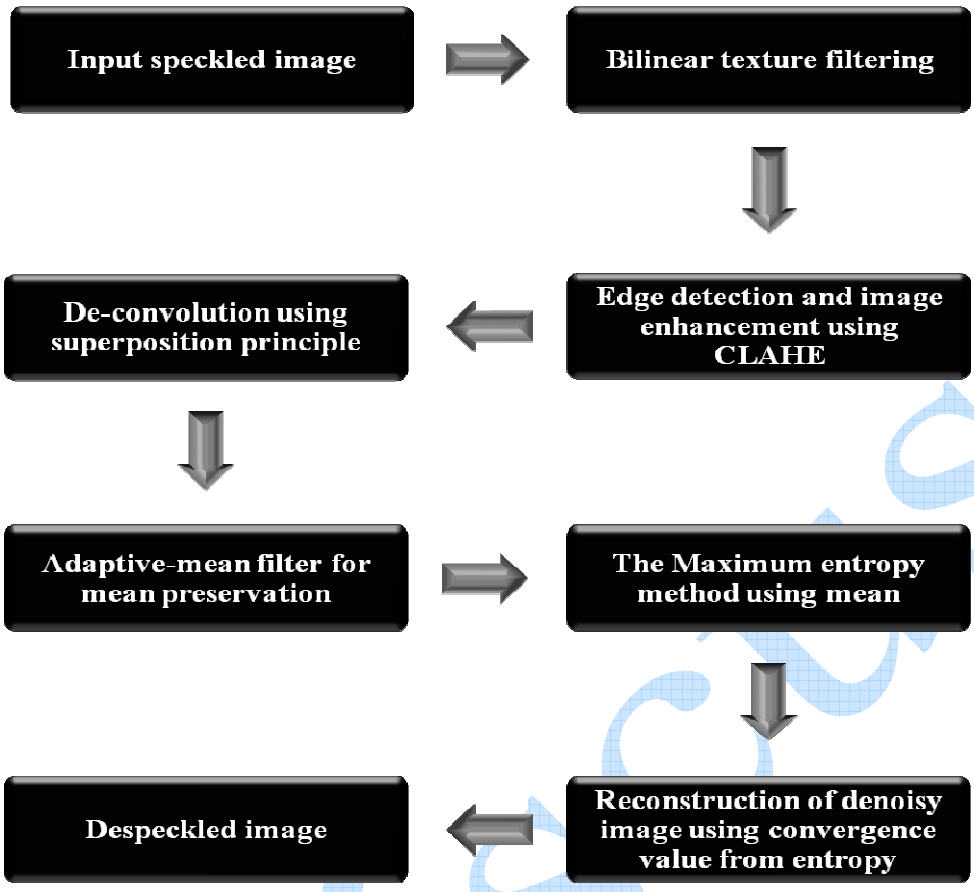


Figure 1. Flow Diagram of Recursive Filter

5.2.3 Clahe

Contrast limited adaptive histogram equalization (CLAHE) was originally developed for medical imaging and has proven to be successful for enhancement of low-contrast images. The CLAHE algorithm partitions the images into contextual regions and applies the histogram equalization to each one. This evens out the distribution of used grey values and thus makes hidden features of the image more visible.

5.2.4 Deconvolution

Deconvolution is an algorithm-based process used to reverse the effects of convolution on recorded data. In general, the object of deconvolution is to find the solution of a convolution equation of the form:

$$f * g = h \quad (3)$$

Usually, h is some recorded signal, and f is some signal that we wish to recover, but has been convolved with some other signal g before we recorded it. The function g might represent the transfer function of an instrument or a driving force that was applied to a physical system. In physical measurements, the situation is usually closer to

$$(f * g) + \varepsilon = h \quad (4)$$

In this case ε is noise that has entered our recorded signal. If we assume that a noisy signal or image is noiseless when we try to make a statistical estimate of g, our estimate will be incorrect. In turn, our estimate of f will also be incorrect. The lower the signal-to-noise ratio, the worse our estimate of the deconvolved signal will be. That is the reason why usually inverse filtering the signal is not a good solution. However, if we have at least some knowledge of the type of noise in the data (for example, white noise), we may be able to improve the estimate of f through techniques such as Wiener deconvolution.

5.2.5 Adaptive Mean Filter

The idea of mean filtering is simply to replace each pixel value in an image with the mean (‘average’) value of its neighbors, including itself. This has the effect of eliminating pixel values which are unrepresentative of their surroundings. Adaptive mean filter performs as a mean filter if no edge

crossings are detected in the moving window, otherwise, it only computes the mean within the peak or valley region where the current pixel is located if one or more edge crossings are detected in the moving window. It guarantees the preservation of the mean.

5.2.6 Maximum Entropy Method

The Maximum Entropy method (MEM) is a pixel-based deconvolution algorithm that performs a rigorous constrained optimization in a basis of pixel amplitudes. MEM uses the Bayesian formulation of chi-square minimization, and applies a penalty function based on relative image entropy.
This choice of penalty function biases the estimate of the true sky brightness towards a known prior image. If a flat image is chosen as the prior, the solution is biased towards being smooth, and produces a more realistic reconstruction of extended emission. Positivity and emptiness constraints can be applied on the image pixels via a penalty function.
The maximum entropy method extracts as much information from a measurement as is justified by the data's signal-to-noise ratio. For data that are linearly related to the desired image, the maximum entropy method solution is unique; there is no multiple minimum problem.

5.3 Recursive Filter Simulation

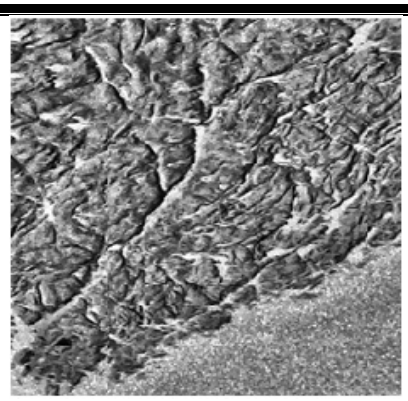
The Recursive filter is applied for the input simulated speckled image as shown in fig.2 and fig.3 and the parameters are calculated for the input and output as shown in table 1 and 2. The image is despeckled by recursive filtering and the parameters are calculated and tabulated.

Table 1. Parameters calculated in recursive filter (Norway)

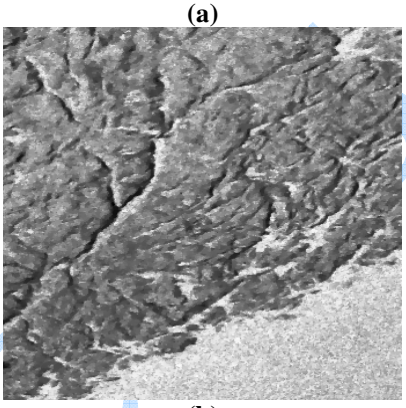
Parameters	Speckled image	Despeckled image
Mean	141.29	141.29
Standard deviation	58.57	47.85
RMSE	9.91	8.70
PSNR(dB)	28.21	29.34

Table 2. Parameters calculated in recursive filter (Pentagon)

Parameters	Speckled image	Despeckled image
Mean	92.69	92.63
Standard deviation	45.79	35.02
RMSE	9.08	8.00
PSNR(dB)	28.97	30.07



(a)



(b)

Figure 2. Recursive filter (Norway) (a) Speckled image (b) Despeckled image

(a)

(b)

Figure 3. Recursive filter (Pentagon) (a) Speckled image (b) Despeckled image

It is inferred from the tabular column that despeckling by recursive filtering, preserves the

mean, reduces standard deviation and RMSE and increases the PSNR.

6. MODEL BASED DESPECKLING

A new Bayesian approach for speckle reduction in SAR images is proposed. The emphasis lies on speckle removal without losing textural and structural information. Textural properties contained in the image must be recognized to be accurately reconstructed in the filtered image. For this reconstruction a new despeckling and information extraction algorithm that uses Gauss Markov random fields (GMRFs) as texture models and takes advantage of both the first and the second level of Bayesian inference to obtain a maximum a posteriori (MAP) estimate of the noise-free image.

6.1 Flow Diagram of Model Based Despeckling

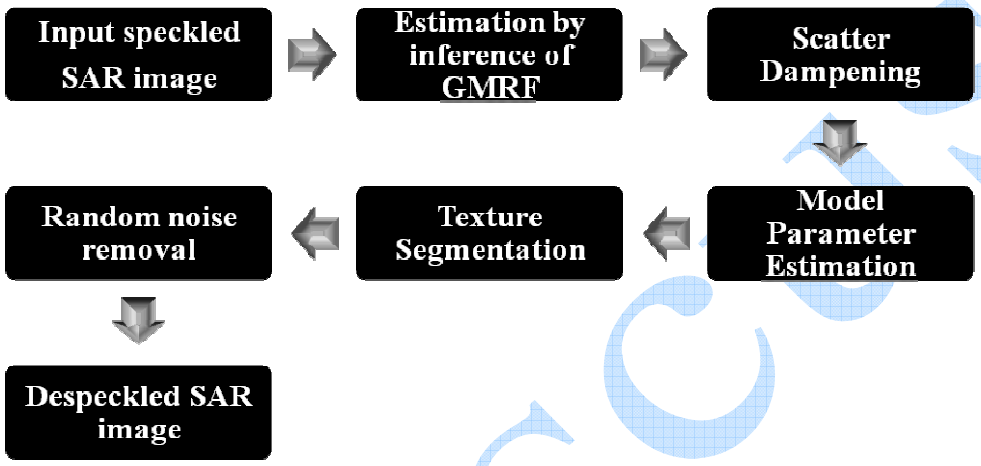


Figure 4. Flow Diagram of Model based Despeckling

6.2 Bayesian Inference

Bayesian inference is a method of statistical inference in which some kinds of evidence or observations are used to calculate the probability that a hypothesis may be true, or else to update its previously-calculated probability. In practical usage, "Bayesian inference" refers to the use of a prior probability over hypotheses to determine the likelihood of a particular hypothesis given some observed evidence.

6.2.1 Gaussian Markov Random Field Models

Markov random field (MRF) models have been extensively used in image modeling to characterize prior beliefs about various image features such as textures, edges, region labels etc. and have been applied for restoration, segmentation and other image processing problems. Gaussian Markov random fields (GMRFs) are simply multivariate. A GMRF is a simple construct. A normal distributed random vector x = (x1; ... ; xn)^T.

6.2.2 Maximum-A-Posteriori (MAP) Estimation

In Bayesian statistics, a maximum a posteriori probability (MAP) estimate is a mode of the posterior distribution. The MAP can be used to obtain a point estimate of an unobserved quantity on the basis of empirical data. MAP estimation can be seen as a regularization of ML estimation. Sometimes a priori information about the physical process whose parameters is to be estimated is available. Such information can come either from the correct scientific knowledge of the physical process or from previous empirical evidence. These can be encoded from such prior information in terms of a PDF on the parameter to be estimated. Essentially, the parameter θ is treated as the value of an RV. The associated probabilities P(θ) are called the prior probabilities. The inference based on such priors as Bayesian inference is referred. Baye's theorem shows the way for incorporating prior information in the estimation process:

$$P(\theta|\mathbf{x}) = \frac{P(\mathbf{x}|\theta)P(\theta)}{P(\mathbf{x})} \quad (5)$$

The term on the left hand side of the equation is called the posterior. On the right hand side, the numerator is the product of the likelihood term and the prior term. The denominator serves as a normalization term so that the posterior PDF

integrates to unity. Thus, Bayesian inference produces the maximum a posteriori (MAP) estimate.

6.2.3 Parameter Estimation

6.2.3.1 The Expectation-Maximization Algorithm

The EM algorithm is an efficient iterative procedure to compute the Maximum Likelihood (ML) estimate in the presence of missing or hidden data. In ML estimation, the model parameter(s) for which the observed data are the most likely are estimated. Each iteration of the EM algorithm consists of two processes: The E-step, and the M-step.

In statistics, an expectation-maximization (EM) algorithm is a method for finding maximum likelihood or maximum a posteriori (MAP) estimates of parameters in statistical models, where the model depends on unobserved latent variables. EM is an iterative method which alternates between performing an expectation (E) step, which computes the expectation of the log-likelihood, evaluated using the current estimate for the latent variables, and maximization (M) step, which computes parameters maximizing the expected log-likelihood found on the E step. These parameter-estimates are then used to determine the distribution of the latent variables in the next E step.

6.2.3.2 Properties

Speaking of an expectation (E) step is a bit of a misnomer. What is calculated in the first step are the fixed, data-dependent parameters of the function Q. Once the parameters of Q are known, it is fully determined and is maximized in the second (M) step of an EM algorithm. For multimodal distributions, this means that an EM algorithm may converge to a local maximum of the observed data likelihood function, depending on starting values.

The EM method was modified to compute maximum a posteriori (MAP) estimates for Bayesian inference. There are other methods for finding maximum likelihood estimates, such as gradient descent, conjugate gradient or variations of the Gauss–Newton method. Unlike EM, such methods typically require the evaluation of first and/or second derivatives of the likelihood function.

6.3 Texture Segmentation

Texture can be arranged along a spectrum going from stochastic to regular:

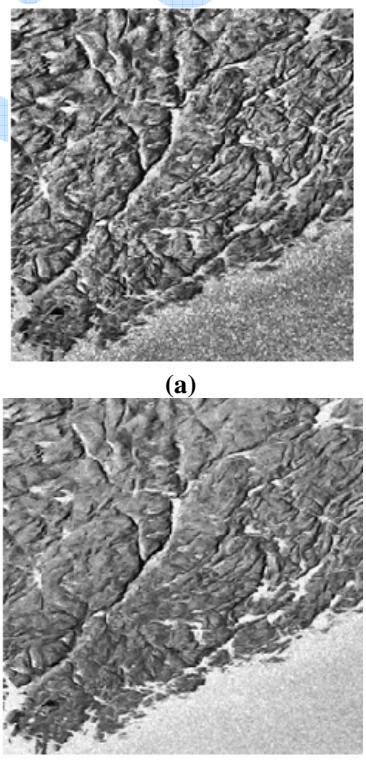
Stochastic textures: Texture images of stochastic textures look like noise: colour dots that are randomly scattered over the image, barely specified by the attributes minimum and maximum brightness and average colour. Many textures look like stochastic textures when viewed from a distance. An example of a stochastic texture is roughcast.

Structured textures: These textures look like somewhat regular patterns. An example of a structured texture is a stonewall or a floor tiled with paving stones. Texture segmentation problem is assigning a label, say from (1, 2, . . . , V) to the sites on the lattice, where the label stands for the texture class to which the site belongs to.

Different textures in an image are modeled by GMRF models with different parameters represented by (Q(v),a2(v)), v E { 1 , 2 , . . .V}.

6.4 Model Based Simulation

The Model based despeckling is applied for the input simulated speckled image as shown in fig.5 and fig.6 and the parameters are calculated for the input and output as shown in table 3 and table 4. The image is despeckled by model-based despeckling and the parameters are calculated and tabulated.



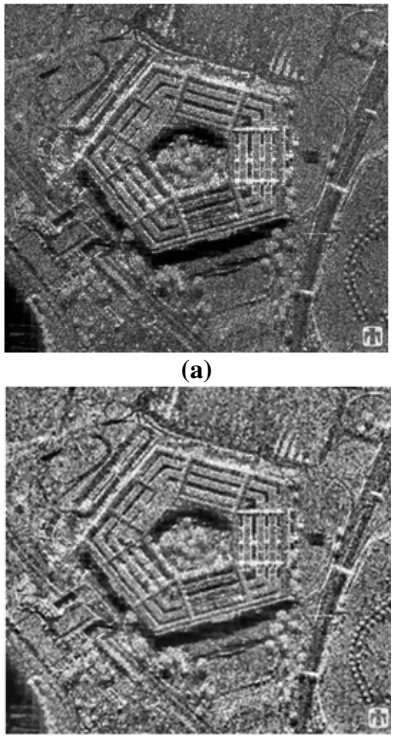
(a)

(b)

Figure 5. Model based (Norway) (a) Speckled image (b) Despeckled image

Table 3. Parameters calculated in model based (Norway)

Parameters	Speckled image	Despeckled image
Mean	141.29	141.38
Standard deviation	58.57	54.77
RMSE	9.91	9.29
PSNR(dB)	28.21	28.77



(a) **(b)**

Figure 6. Model based (Norway) (a) Speckled image (b) Despeckled image

Table 4. Parameters calculated in model based (Pentagon)

Parameters	Speckled image	Despeckled image
Mean	92.69	92.34
Standard deviation	45.79	42.79
RMSE	9.08	8.43
PSNR(dB)	28.97	29.62

It is inferred from the tabular column that despeckling by model based despeckling, preserves the mean, reduces standard deviation and RMSE and increases the PSNR.

8. ANISOTROPIC DIFFUSION

8.1 Diffusion Filtering

Diffusion filters are designed to smooth homogeneous image regions to reduce noise, while preserving edges. However with the increase of diffusion, the smoothing applied to homogeneous regions might not stop at its boundaries, leading to a blurring effect. This effect distorts image features and dislocates their edges.

8.2 Flow Diagram of Anisotropic Diffusion

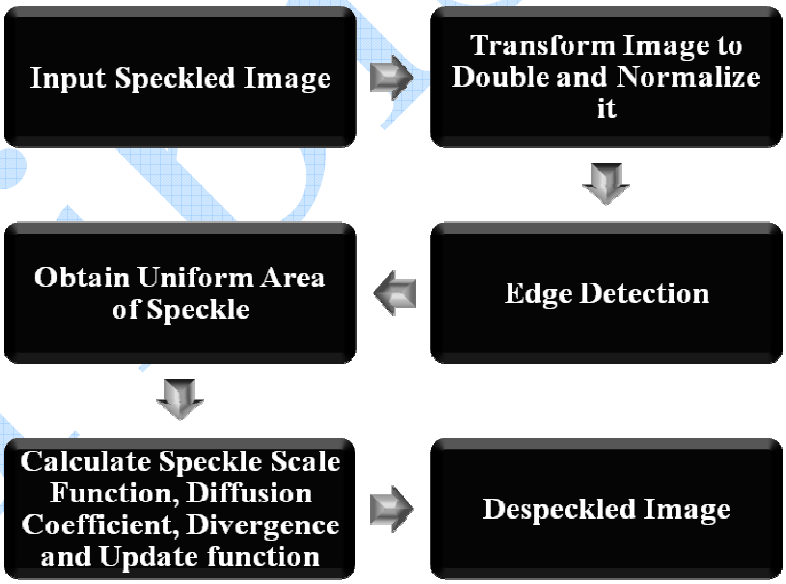


Figure 7. Flow Diagram of Anisotropic Diffusion

8.2.1 Explanation of the Block Diagram

Anisotropic diffusion is normally implemented by means of an approximation of the generalized diffusion equation: each new image in the family is computed by applying this equation to the previous image. Consequently, anisotropic diffusion is an iterative process where a relatively simple set of computation are used to compute each successive image in the family and this process is continued until a sufficient degree of smoothing is obtained.

8.2.2 Edge Detection

The Sobel operator is used in image processing, particularly within edge detection algorithms. It is a

discrete differentiation operator, computing an approximation of the gradient of the image intensity function. At each point in the image, the result of the Sobel operator is either the corresponding gradient vector or the norm of this vector.
The Sobel operator is based on convolving the image with a small, separable, and integer valued filter in horizontal and vertical direction and is therefore relatively inexpensive in terms of computations. On the other hand, the gradient approximation which it produces is relatively crude, in particular for high frequency variations in the image.
The operator calculates the gradient of the image intensity at each point, giving the direction of the largest possible increase from light to dark and the rate of change in that direction. The result therefore shows how "abruptly" or "smoothly" the image changes at that point and therefore how likely it is that that part of the image represents an edge, as well as how that edge is likely to be oriented.

8.3 Anisotropic Diffusion Basic Theory

Anisotropic diffusion algorithms remove noise from an image by modifying the image via a partial differential equation. Given an intensity image $I_0(x,y)$ having finite power and no zero values over the image support Ω, the output image $I(x,y;t)$ is evolved according to the following PDE:

$$\begin{cases} \partial I(x,y;t)/\partial t = \mathrm{div}[c(q)\nabla I(x,y;t)] \\ I(x,y;0) = I_0(x,y),\ (\partial I(x,y;t)/\partial n)|_{\partial\Omega} = 0 \end{cases} \quad (9)$$

where $\partial\Omega$ denotes the border of Ω, n is the outer normal to the $\partial\Omega$.This PDE-based speckle removal approach allows the generation of an image scale space (a set of filtered images that vary from fine to coarse) without bias due to filter window size and shape.

8.5 Discretization

The above differential equation may be solved numerically using an iterative Jacobi method. Assuming a sufficiently small time step size of Δt and sufficiently small spatial step size of h in x and y directions, this discretization in the time and space coordinates is calculated in the following manner:

$t = n\Delta t, \quad n = 0,1,2,\ldots..$ (10)
$x = ih \quad i = 0,1,2,\ldots.M-1$ (11)
$y = jh \quad j = 0,1,2,\ldots.N-1$ (12)

where Mh×Nh is the size of the image support.The diffusion coefficient is given by

$$c(q) = \frac{1}{1+[e^2(x,y;t)-q_0^2(t)]/[q_0^2(t)(1+q_0^2(t))]} \quad (13)$$

where $e^2(x,y;t)$ is the edge detector and $q_0(t)$ is the speckle scale function.
The speckle scale function $q_0(t)$ effectively controls the amount of smoothing applied to the image. It is estimated using

$$q_0(t) = \frac{sqrt(\mathrm{var}[z(t)])}{z(t)} \quad (14)$$

where var[z(t)] and z(t) are the intensity variance and mean over a homogeneous area at t , respectively. This diffusion filtering requires knowing a homogeneous area inside the image being processed. The divergence is

$$d_{i,j} = [\, c_{i+1,j}(I_{i+1,j} - I_{i,j}) + c_{i,j}(I_{i-1,j} - I_{i,j}) + c_{i,j+1}(I_{i,j+1} - I_{i,j}) + c_{i,j}(I_{i,j-1} - I_{i,j})] / h^2 \quad (15)$$

with symmetric boundary conditions:

$d_{-1,j} = d_{0,j} \quad d_{M,j} = d_{M-1,j} \quad j=0,1,2,\ldots.,N-1$
$d_{i,-1} = d_{i,0} \quad d_{i,N} = d_{i,N-1} \quad i=0,1,2,\ldots.,M-1$

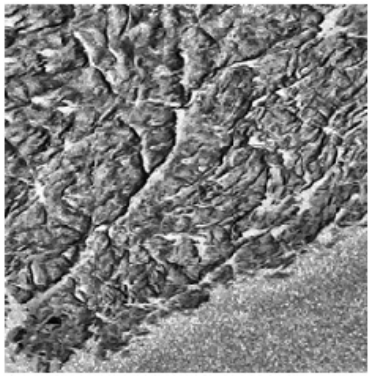
Finally, by approximating time derivative with forward differencing, the numerical approximation to the differential equation is given by

$$Ii,j = Ii,j + \Delta t\, di,j / 4 \quad (16)$$

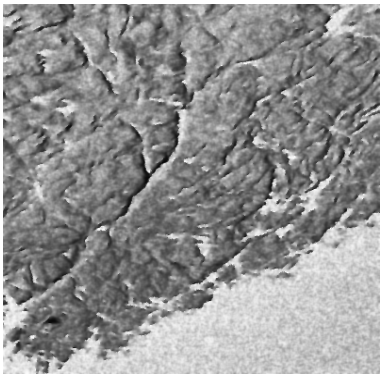
This is called the SRAD update function. In numerical implementation, h=1 and Δt=0.05 is chosen, since the diffusion coefficient will not be exactly equal to zero at any edge in a digital image, and set it to be zero if it is less than a lower threshold, to better stop diffusion across main edges.

8.6 Anisotropic Diffusion Simulation

The Anisotropic diffusion is applied for the input simulated speckled image as shown in fig.8 and fig.9 and the parameters are calculated for the input and output as shown in table 5 and table 6. The image is despeckled by model-based despeckling and the parameters are calculated and tabulated.



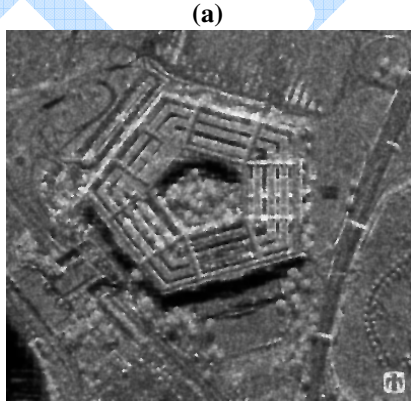
(a)



(b)

Figure 8. Anisotropic diffusion (Norway)
(a) Speckled image (b) Despeckled image

(a)



(b)

Figure 9. Anisotropic diffusion (Pentagon)
(a) Speckled image (b) Despeckled image

Table 5. Parameters calculated in anisotropic diffusion (Norway)

Parameters	Speckled image	Despeckled image
Mean	141.29	143.81
Standard deviation	58.57	46.87
RMSE	9.91	7.66
PSNR(dB)	28.21	30.44

Table 6. Parameters calculated in anisotropic diffusion (Pentagon)

Parameters	Speckled image	Despeckled image
Mean	92.69	94.72
Standard deviation	45.79	34.25
RMSE	9.08	7.45
PSNR(dB)	28.97	30.69

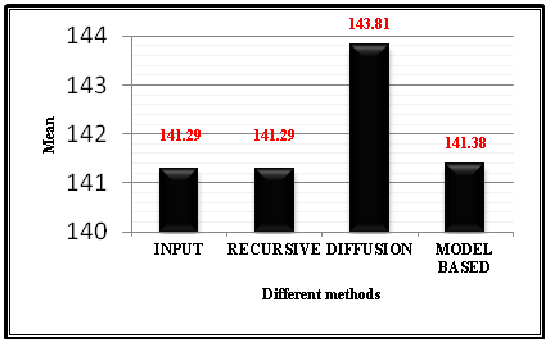
It is inferred from the tabular column that despeckling by anisotropic diffusion, preserves the mean, reduces standard deviation and RMSE and increases the PSNR.

9. Results and Discussion

The images are despeckled with the three algorithms and results are compared.

9.1 Comparison Graphs (Norway)

For the four parameters calculated by three methods, a comparison graph is drawn.



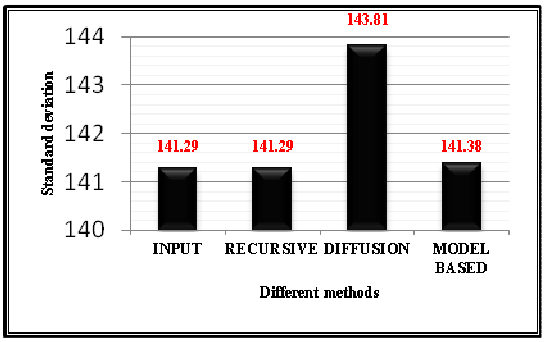
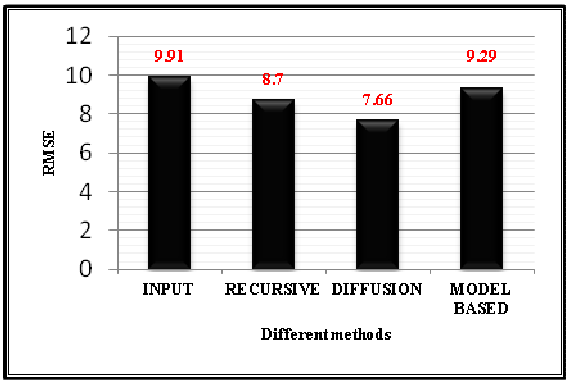


Figure 10. Graphical representation of Comparison of Mean and Standard deviation (Norway)



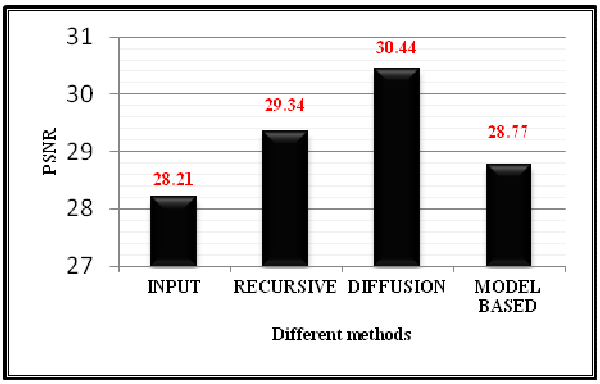
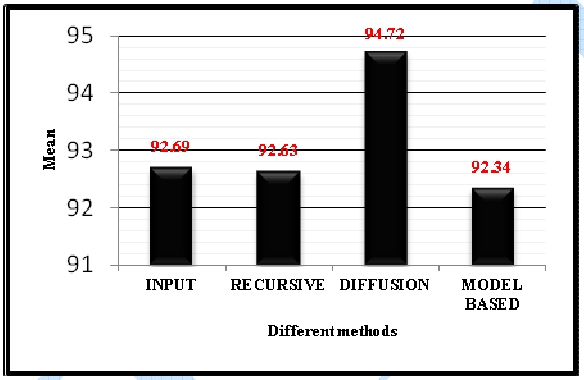


Figure 11. Graphical representation of Comparison of RMSE and PSNR (Norway)

9.2 Comparison Graphs(Pentagon)



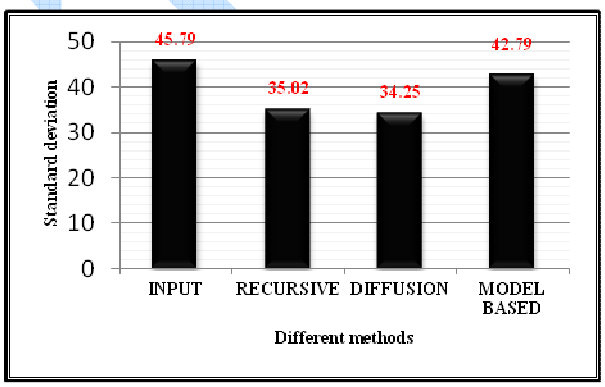
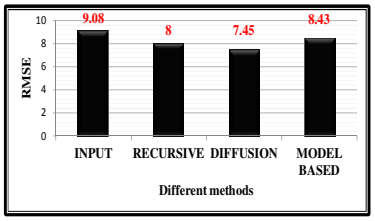


Figure 12. Graphical representation of Comparison of Mean and Standard deviation (Pentagon)

It is observed from the graph that mean is preserved in recursive filtering. On observing the comparison graph of standard deviation, it is greatly reduced in anisotropic diffusion.



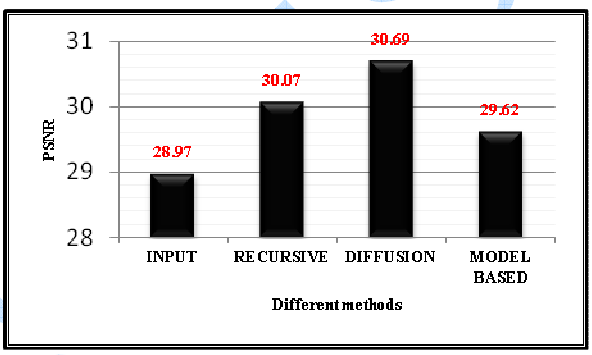


Figure 13. Graphical representation of Comparison of RMSE and PSNR (Pentagon)

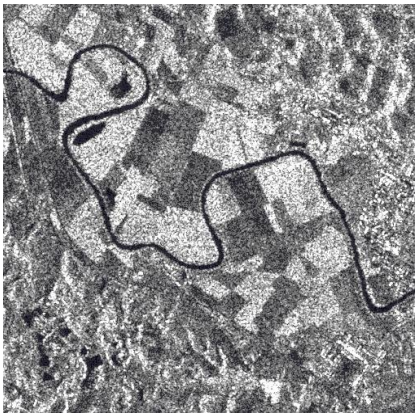
From the above graphs it is clear that RMSE is reduced and PSNR value is increased in anisotropic diffusion method. Thus for despeckling of geographical images anisotropic diffusion is an efficient method.

9.3 Despeckling of Original SAR Image

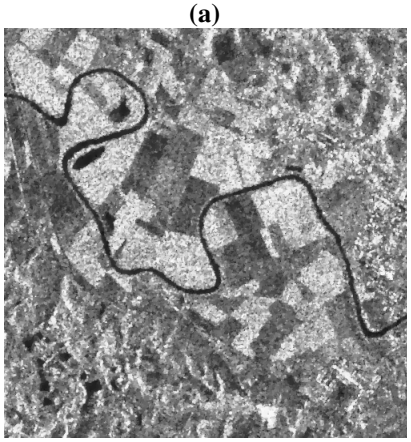
The following figure (a) is a real SAR image taken by ERS satellite. The three despeckling methods are applied to the real SAR image and the parameters are calculated as shown in table 7.

Table 7. Parameter calculations for original SAR image

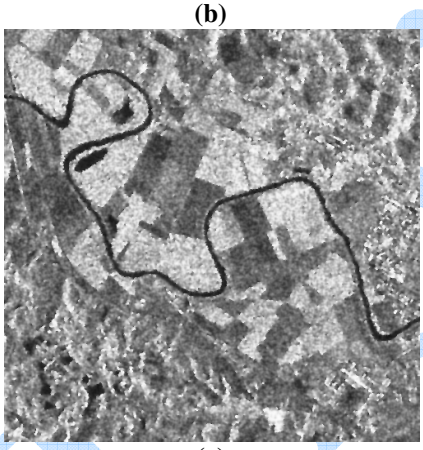
Parameters	Recursive filtering	Model based	Anisotropic diffusion
Mean	137.87	137.83	140.47
Standard deviation	49.44	57.23	47.97
RMSE	9.25	6.53	9.27
PSNR(dB)	28.81	31.82	28.79



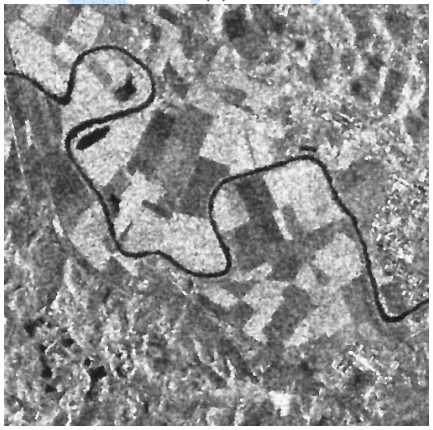
(a)



(b)



(c)



(d)

Figure 14. Speckled and Despeckled images (a) Original SAR image (b) Recursive filter (c) Model based (d) Anisotropic diffusion

The Original SAR image is despeckled and the parameters are calculated and tabulated. It is clear from the tabular column that the standard deviation is greatly reduced in anisotropic diffusion, RMSE is reduced in model-based despeckling and PSNR is increased in model-based despeckling.

9.4 Comparison Graphs for original SAR image

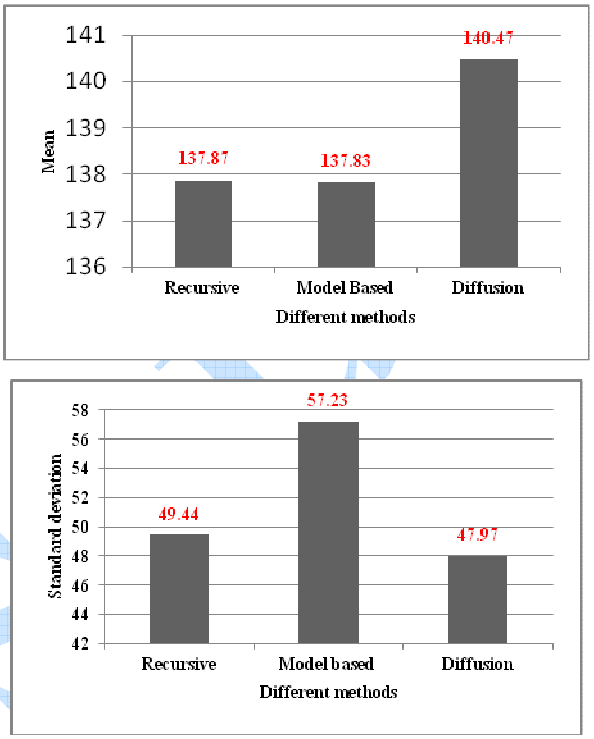


Figure 15. Graphical representation of comparison of Mean and Standard deviation of different methods

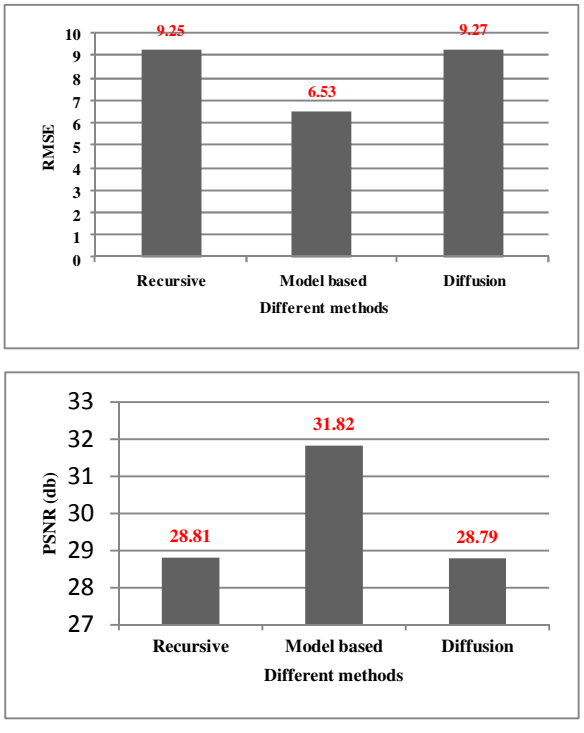


Figure 16. Graphical representation of comparison of PSNR of different methods

On observing the tabular column and comparison graphs, we infer that the model-based despeckling is an efficient method for Original SAR images.

10. Conclusion and Future Scope

10.1 Conclusion

The MATLAB codes for the three despeckling methods are tested with two simulated speckle SAR images: Norway and Pentagon and a original SAR image. The computational time is high for Model based despeckling compared to the others two methods. The Model based despeckling preserves the texture and gives better results for geographical images. Anisotropic diffusion is computationally efficient for real SAR images. Recursive filtering is effective for both real and synthetic SAR images. (This Project was supported by AICTE New Delhi, India under the MODROB scheme)

10.2 Future Scope

The three methods discussed here perform the despeckling operation in spatial domain, directly operating on pixel values. These methods can be implemented in frequency domain using any of the transform, which is operating on the sub band coefficients.

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