STRUCTURE-PRESERVING SPECKLE REDUCTION OF SAR IMAGES USING NONLOCAL MEANS FILTERS

Xuezhi Yang[1] and David A. Clausi[2]

[1]School of Computer and Information, Hefei University of Technology, Hefei, Anhui, China
[2]Systems Design Engineering, University of Waterloo, Waterloo, ON, Canada

ABSTRACT

This paper proposes a structure-preserving speckle reduction (SPSR) algorithm for synthetic aperture radar (SAR) images by exploiting self-similarity of structural patterns based on nonlocal means filter. The SPSR algorithm is featured by discerning pixels of similar structural patterns, which is crucial for a despeckling process to avoid blurring image structure. To alleviate the impact of speckle noise to similarity measure, a two-stage filtering scheme is introduced into the SPSR algorithm. Filtering at the first stage aims at an accurate approximation of true structural similarity, followed by the filtering at the second stage to group pixels with similar neighborhood in a large area. Compared to the traditional Lee filter, enhanced Lee filter and the speckle reducing anisotropic diffusion (SRAD), evaluation results have shown that the SPSR algorithm substantially improves the despeckling performance especially on structure preservation and speckle reduction in homogeneous regions.

***Index Terms*—**Synthetic aperture radar (SAR), speckle reduction, nonlocal means

1. INTRODUCTION

Synthetic aperture radar (SAR) images are corrupted by speckle noise due to the coherent nature of the radar imaging process. Over the past decades, speckle reduction remains to be a major concern in SAR image processing with two objectives in focus: 1) speckle reduction in homogeneous regions; 2) preservation of structure information, including edges and textures, which are of crucial importance for accurate interpretation and classification of SAR images.

A large number of filters have been developed to suppress speckle noise in SAR images. Some well-known speckle filters, including Lee [1] and enhanced Lee [2] etc., adopt window-based local statistics to measure average intensity similarity between pixels while weakly discern the difference between edges and their neighborhood pixels. Further improvements on edge preservation can be achieved by incorporating local gradient information into despeckling process as edge-sensitive features, such as the speckle reducing anisotropic diffusion (SRAD) [3] and wavelet denoising methods [4]. The gradient information can be used to enhance the discrimination of edges in SAR images while is insufficient for preserving fine textures. Gaussian Markov random field (GMRF) model [5,8] has also been applied to the despeckling process. Though improvements on texture preservation are obtained, the GMRF model still suffers from poor restoration of edges.

As a problem common to these speckle filters, pixels belonging to the same type of structural patterns (edges, texture primitives and homogeneous regions) cannot be faithfully identified, which causes false mixture of different structural components in the despeckling process and hence degrades the preservation of structures.

This paper proposes a structure-preserving speckle reduction (SPSR) algorithm for SAR images based on the nonlocal means (NL-means) filter [6], which has two distinctive advantages over various existing despeckling filters. First, the SPSR algorithm compares pixels with respect to their neighborhood patches, which can discern pixels of similar structural patterns rather than the commonly used rough classification between homogeneous regions and edges. Second, Self-similarity or redundancy of structural patterns in a large area is utilized for the restoration of original image, which offers a more reliable reduction of speckle noise than the traditional local schemes.

The true structural similarity between pixels is highly desired for the proposed SPSR algorithm which however has to be estimated in noisy SAR images. To alleviate the impact of speckle noise to similarity measure, a two-stage filtering scheme is introduced into the SPSR algorithm. Filtering at the first stage aims at an accurate approximation of true structural similarity, followed by the filtering at the second stage to group pixels with similar neighborhood in a large area.

In the next section, the SPSR algorithm is presented. The two-stage filtering scheme for approximating the true structural similarity is then presented in Section 3, followed by evaluations of the proposed method in Section 4. This paper is concluded in Section 5.

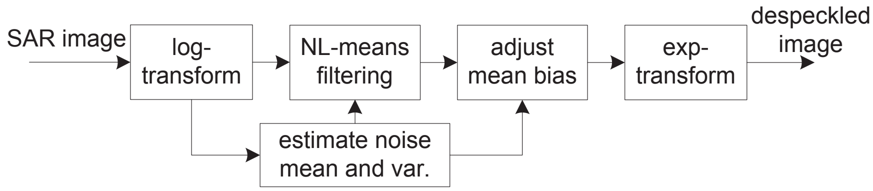


Figure 1. The structure-preserving speckle reduction (SPSR) algorithm

2. STRUCTURE-PRESERVING SPECKLE REDUCTION (SPSR) ALGORITHM

The proposed SPSR algorithm is illustrated in Fig. 1. Since the NL-means filter is originally designed for removing additive white noise, an additive SAR image model is first built based on the logarithmic transform, which converts multiplicative speckle noise to additive white Gaussian noise (AWGN). The NL-means filtering is then used to suppress the transformed speckle noise. To restore the original radiometric properties of the SAR image, the filtering result in log-transformed domain is converted by first correcting the mean bias introduced by the nonlinear logarithmic transform and then applying the exponential transform. Statistical properties of speckle noise in log-transformed domain are derived to facilitate the NL-means filtering process as well as the restoration of SAR images.

2.1. Additive SAR Image Model

SAR image intensity, corrupted by the multiplicative speckle noise, can be represented by the following model:

$$I = XS\,, \tag{1}$$

where I indicates observed intensity of the SAR image and X denotes backscattering coefficients. S denotes the speckle noise and follows a Gamma distribution with unit mean and variance $1/L$, given the SAR image is an average of L looks.

The natural logarithmic transformation of (1) gives

$$\ln(I) = \ln(X) + \ln(S)\,, \tag{2}$$

which converts the model from multiplicative to additive. Mean and variance of the log-transformed speckle noise are given as follows [4]:

$$\mu = E(\ln(S)) = \Psi(L) - \ln(L), \quad \sigma^2 = \mathrm{var}(\ln(S)) = \Psi(1, L), \tag{3}$$

where $\psi(L)$ denotes the Digamma function and $\psi(1,L)$ is the first-order Polygamma function. For L being an integer, (3) can be simplified as

$$\mu = \sum_{k=1}^{L-1} \frac{1}{k} + \Psi(1) - \ln(L), \quad \sigma^2 = \Psi(1,1) - \sum_{k=1}^{L-1} \frac{1}{k^2}\,. \tag{4}$$

It has been revealed that [4], along with the increase of the number of looks, the probability density function of log-transformed speckle noise approximates the Gaussian distribution. Therefore, the speckle noise can be further converted to equivalent additive white Gaussian noise (AWGN) in the following additive SAR image model:

$$y = x + n\,, \tag{5}$$

where y=ln(I), x=ln(X)+E(ln(S)), and n= ln(S)-E(ln(S)) is the AWGN term.

2.2. NL-means Filter-Based Speckle Reduction

The NL-means filter was recently proposed by Buades et al. [6] for removing additive image noise by exploiting self-similarity in images, which has been shown to provide state-of-the-art denoising performance in contrast to various other algorithms.

Based on the additive noise model (5), let $y(i)$ be the value of a pixel indexed i in the noisy image Y, the restored value $x^*(i)$ using the NL-means filter is a weighted average of all pixels in the image:

$$x^*(i) = \sum_{j \in Y} w(i, j) y(j)\,, \tag{6}$$

where the weight $w(i,j)$ measures the structural similarity between pixels i and j, and can be computed as follows:

$$w(i, j) = \frac{1}{Z(i)} e^{-\frac{\|y(N_i) - y(N_j)\|^2}{h^2}}\,, \tag{7}$$

where $Z(i)$ is a normalizing factor. N_i denotes a neighborhood of pixel i which is normally defined as a fixed-size window centered on the pixel. $y(N_i)$ is a vector representation of the image patch on the neighborhood N_i. $\|\cdot\|^2$ denotes the Euclidean distance between two image patches surrounding pixels i and j respectively. h is a parameter controlling the decay of the patch-based Euclidean distance and subsequently the degree of smoothing, which is set up as $0.5^*\sigma^2$.

After applying the NL-means filtering, the final step of the SPSR algorithm is to restore the noise-free backscattering coefficients X from the filtering result in the log-transformed domain as follows:

$$X^* = \exp\left(x^* - E(\ln(S))\right). \tag{8}$$

3. THE SPSR ALGORITHM WITH REFINED STRUCTURAL SIMILARITY

The success of the SPSR algorithm relies on accurately locating pixels sharing the same structural pattern in the image, while the similarity has to be measured in the noisy SAR image and is hence distorted by speckle noise. Assuming the white Gaussian noise n in (5) is i.i.d, the Euclidean distance-based similarity measure in the noise-free image x and the noisy image y has the following relationship:

$$E\left\|y(N_i)-y(N_j)\right\|^2=\left\|x(N_i)-x(N_j)\right\|^2+2\sigma^2, \quad (9)$$

which indicates the degree of bias introduced by the noise in estimating pixel similarity in SAR images. Specifically, pixels whose similarity measures have small values seriously deviate from the true values. These pixels are typically at the homogeneous regions as well as features with low intensity variations, where the speckle reduction performance of the SPSR algorithm hence degrades.

To alleviate the impact of speckle noise to similarity measure, we propose a two-stage NL-means filtering-based SPSR algorithm. Based on the additive SAR image model (5), the NL-means filtering in the first stage aims at facilitating the estimate of pixel similarity by converting the noisy image y into a new representation u as follows:

$$u(i)=\sum_{j\in Y} w_1(i,j)y(j),\ w_1(i,j)=\frac{1}{Z_1(i)}e^{-\frac{\left\|y(N_i)-y(N_j)\right\|^2}{h_1^2}} \quad (10)$$

where $Z_1(i)$ is the normalizing factor. The similarity measure can be refined on u rather than on the noisy image:

$$w_2(i,j)=\frac{1}{Z_2(i)}e^{-\frac{\left\|u(N_i)-u(N_j)\right\|^2}{h_2^2}}, \quad (11)$$

where $Z_2(i)$ is the normalizing factor. $w_2(i,j)$ is then fed into the NL-means filtering process in the second stage for despeckling purpose, which restores the true pixel value $x(i)$ by

$$x^*(i)=\sum_{j\in Y} w_2(i,j)y(j). \quad (12)$$

The filtering in the first stage adopts a small value for the smoothing parameter h_1 to preserve the dissimilarity between pixels of different structures. Since the impact of speckle noise is primarily on pixels of small difference, a small h_1 is sufficient for restoring their true similarity. Based on the first stage NL-means filtering result, similarity measures for pixels of the same structures are reduced relative to that on the noisy image. Therefore, the smoothing parameter h_2 in the second stage filtering should be smaller than h used in (7) to avoid over-smoothing. In this work, both h_1 and h_2 are set up as $0.15{*}\sigma^2$.

4. TESTING AND RESULTS

The proposed SPSR algorithm is tested by measuring pixel similarity on the noisy image (noisy similarity-based SPSR, NS-SPSR) and the NL-means filtering (two-stage NL-means-based SPSR, TSNLM-SPSR) respectively, and compared with the Lee filter [1], the enhanced Lee filter [2] as well as the SRAD algorithm [3].

The first test is on the Lena image shown in Fig. 2. The Lena is corrupted by multiplying spatially uncorrelated speckle noise with the number of looks (L) of 5, 10 and 20 respectively. Three criteria are used for a quantitative evaluation of the despeckling performance: S/MSE [4], equivalent number of looks (ENL) [4] and edge correlation coefficient (ECC) [7]. The S/MSE measures the overall despeckling performance, while the ENL indicates speckle reduction in homogeneous regions. The ECC is used to evaluate the preservation of structures in terms of the gradient correlation between the original image and its despeckled result.

Using the Lee filter, the enhanced Lee filter, the SRAD and the proposed SPSR algorithm, despeckling performance are summarized in Table I. In contrast to the first three filters, the NS-SPSR achieves better despeckling performance in terms of the S/MSE, the ECC and the ENL, showing the advantages of discrimination of local structures for speckle reduction. By refining the structural similarity measure, the TSNLM-SPSR further obtains a noticeable improvement increasing with the level of speckle noise, especially on speckle reduction in homogeneous regions and the structural preservation. An example of speckle reduction on the noisy Lena using various filters is shown in Fig. 3.

The second test is on a real SAR image shown in Fig. 4a in part. A repetitive texture pattern can be visually identified. This pattern is totally blurred in the SRAD filtering result (Fig. 4b), while is efficiently recovered by the NS-SPSR (Fig. 4c) especially when the TSNLM-SPSR is used(Fig. 4d).

5. CONCLUSIONS

This paper presents a structure-preserving speckle reduction (SPSR) algorithm. In contrast to existing speckle filters, the SPSR algorithm has a distinct advantage of discerning pixels of similar local structures, leading to improved despeckling performance as demonstrated by the testing results. By using the proposed two-stage filtering scheme, the impact of the speckle noise on similarity measures is alleviated which further improves the performance of the SPSR algorithm especially on speckle reduction in homogeneous regions and structure preservation.

ACKNOWLEDGMENT

This work has been supported by the NSERC Networks of Centres of Excellence (NCE) called GEOIDE (Geomatics for Informed Decisions), as well as CRYSYS (CRYospheric SYStem in Canada).
The work of the first author is supported by the National Natural Science Foundation of China (No. 60672120).

6. REFERENCES

[1] J. S. Lee, "Digital image enhancement and noise filtering by use of local statistics", *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. PAMI-2, pp. 165-168, 1980..

[2] A. Lopes, R. Touzi and E. Nezry, “Adaptive speckle filters and Scene heterogeneity”, *IEEE Trans. Geosci Remote Sensing*, 28(6), pp. 992-1000, 1990.

[3] Y. Yu and S. T. Acton, "Speckle reducing anisotropic diffusion", *IEEE Trans. Image Processing*, 11(11), pp. 1260-1270, 2002.

[4] H. Xie, L. E. Pierce and F. T. Ulaby, "SAR speckle reduction using wavelet denoising and markov random field modeling", *IEEE Trans. Geosci Remote Sensing*, 40(10), pp. 2196-2211, 2002.

[5] M. Walessa and M. Datcu, "Model-based despeckling and information extraction from SAR images", *IEEE Trans. Geosci Remote Sensing*, 38(6), pp. 2258-2269, 2000.

[6] A. Buades, B. Coll and J. M. Morel, "A review of image denoising algorithm, with a new one", *Multiscale Modeling and Simulation*, 4(2), pp. 490-530, 2005.

[7] F. Sattar, L. Floreby, G. Salomonsson and B. Lovstrom, "Image enhancement based on a nonlinear multiscale method", *IEEE Trans. Image Processing*, 6(6), pp. 888-895, 1997.

[8] M. Datcu, K. Seidel and M. Walessa, "Spatial information retrieval from remote-sensing images-Part I: information theoretical perspective", *IEEE Trans. Geosci Remote Sensing*, 36(5), pp. 1431-1445, 1998.

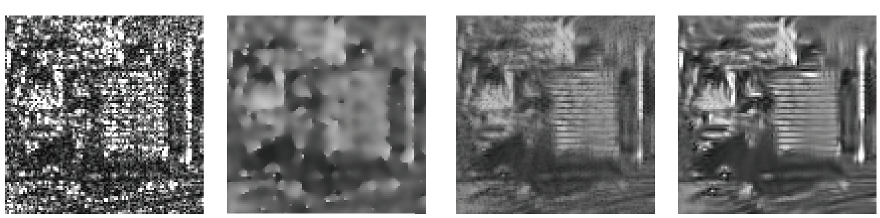
Figure 2. Lena

Table I. Comparison of speckle filters for the Lena image speckled with various levels of noise

L	L = 5			L = 10			L = 20		
	S/MSE	ENL	ECC	S/MSE	ENL	ECC	S/MSE	ENL	ECC
Noisy Image	8.38	5	N/A	10.78	10	N/A	13.38	20	N/A
Lee	16.20	55	0.28	18.90	94	0.49	21.21	201	0.67
Enhanced Lee	19.37	335	0.62	21.42	220	0.71	22.76	388	0.77
SRAD	19.85	404	0.64	22.09	237	0.73	23.92	386	0.80
NS-SPSR	20.34	508	0.65	22.83	411	0.78	24.83	622	0.85
TSNLM-SPSR	21.05	1446	0.76	23.44	623	0.83	25.05	853	0.87

(a) Detail of Lena (b) 5-look speckle noise added (c) SRAD (d) NS-SPSR (e) TSNLM-SPSR

Figure 3. Speckle reduction of the speckled Lena image



(a) Detail of a SAR image (b) SRAD (c) NS-SPSR (d) TSNLM-SPSR

Figure 4. Speckle reduction of a SAR image