SPECKLE NOISE REDUCTION IN SAR IMAGING USING 2-D LATTICE FILTERS BASED SUBBAND DECOMPOSITION

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ABSTRACT

A new speckle reduction algorithm based on 2-D lattice filters for SAR imaging is presented. In the new method, the subband decomposition of the speckled image is performed using 2-D lattice filters. The noisy image is decomposed into subband images using high-pass and low-pass filters having lattice structure, then a threshold value is estimated according to noise variance in each subband and soft-thresholding is applied on the subband images. The despeckled image is obtained from the thresholded subband images using the inverse lattice filters. The proposed speckle reduction method is applied to RADARSAT/SAR images. The performance of the proposed method has also been compared with median filtering, and stationary wavelet transform based speckle reduction methods. Results show that the proposed method may be used efficiently for speckle noise reduction in SAR images.

1. INTRODUCTION

Synthetic Aperture Radar (SAR) systems which are able to operate under all weather conditions have a significant role in the observation and collection of the ground information. However, due to coherent microwave illumination, SAR images are often corrupted by multiplicative speckle noise. Thus, removal of noise without blurring the edges is an important problem in SAR imaging. Classical approaches to speckle noise reduction problem in SAR imaging may be cited as median filtering [1], local statistical methods [2], homomorphic filtering [3] and wavelet based methods [4, 5]. In wavelet based denoising methods, the speckled image is decomposed into subband images using discrete or stationary wavelet transforms, then hard or soft thresholding methods are applied on the these subband images which correspond to wavelet approximation or detail coefficients. The denoised image is obtained by applying the inverse transform on these thresholded subband images. Besides the wavelet based denoising techniques, a new speckle reduction algorithm using a novel multidecomposition approach based on real discrete Fourier transform (RDFT) digital filter bank representation has been presented, recently [6]. In this technique, the low-pass and high-pass subband components are obtained in a tree structure using zero-phase filters implemented by RDFT. The input image is decomposed in multiple levels, and then a threshold value is estimated according to the noise variance in each subband and used for soft-thresholding of the subband coefficients. The denoised image is obtained from the subband images by a new perfect reconstruction algorithm.

In this paper, we present a new speckle reduction algorithm based on 2-D lattice filters for SAR imaging. In the new method, the subband decomposition of the speckled image is performed using 2-D nonseparable lattice filters. Lattice filters are used in digital filter implementations because they have a number of interesting and important properties including modularity, low sensitivity to parameter quantization effects and a simple stability test [7]. Two channel QMF (quadrature mirror filter) bank with lattice structure has perfect reconstruction property, while it guarantees good stop band attenuation for each of the analysis filters. Due to the use of lattice structure a higher order perfect reconstruction QMF bank can be obtained from a lower order perfect reconstruction QMF bank, simply by adding more lattice sections [8]. The analysis section of the complete filter bank is represented by a lattice filter, while the synthesis part is represented by the inverse lattice filter. The noisy image is decomposed into sub-images using high pass and low-pass filters having lattice structure, also appropriate lattice parameters and lattice stages are chosen, then a threshold value is estimated according to noise variance in each subband and soft-thresholding is applied on the subband images. The despeckled image is obtained from the thresholded subband images using the inverse lattice filter.

This paper is organized as follows: brief information about the subband decomposition based on lattice filters is given in Section 2. The proposed speckle reduction method which uses lattice filters based subband decomposition is presented in Section 3. In Section 4, results of 2-D lattice filters based speckle noise reduction and traditional speckle reduction techniques such as median filtering, and stationary wavelet transform (SWT) are given. Section 5 presents general conclusions.

2. REVIEW OF LATTICE FILTERS

2-D lattice filter of [9] has 3 reflection coefficients in every stage and expands by assuming that input data has 4 quadrant symmetry.

The filter has 4 prediction error fields can be defined as recursive input-output equation below.

$$\begin{bmatrix} e_{00}^{(m+1)}(n_1,n_2) \\ e_{10}^{(m+1)}(n_1,n_2) \\ e_{11}^{(m+1)}(n_1,n_2) \\ e_{01}^{(m+1)}(n_1,n_2) \end{bmatrix} = \begin{bmatrix} 1 & -k_1^{(m+1)} & -k_2^{(m+1)} & -k_3^{(m+1)} \\ k_1^{(m+1)} & 1 & -k_3^{(m+1)} & k_2^{(m+1)} \\ -k_2^{(m+1)} & k_3^{(m+1)} & 1 & k_1^{(m+1)} \\ k_3^{(m+1)} & k_2^{(m+1)} & -k_1^{(m+1)} & 1 \end{bmatrix} x \begin{bmatrix} e_{00}^{(m)}(n_1,n_2) \\ e_{10}^{(m)}(n_1-1,n_2) \\ e_{11}^{(m)}(n_1-1,n_2-1) \\ e_{01}^{(m)}(n_1,n_2-1) \end{bmatrix} \quad (1)$$

where (m) = (m1,m2), (m+1) = (m1+1,m2+1) and $n_1 = 1,\ldots\ldots\ldots,N_1$, $n_2 = 1,\ldots\ldots\ldots,N_2$, $m = 1,\ldots\ldots\ldots,M-1$, $k_j^{(m+1)}$ are lattice reflection coefficients of (m+1)th stage. M is the length of filter. The initial conditions are:

$$e_{00}^{0}(n_1,n_2)=e_{10}^{0}(n_1,n_2)=e_{11}^{0}(n_1,n_2)=e_{01}^{0}(n_1,n_2)=x(n_1,n_2) \quad (2)$$

$e_{00}^{(m)}(n_1,n_2)$, $e_{10}^{(m)}(n_1,n_2)$, $e_{11}^{(m)}(n_1,n_2)$ and $e_{01}^{(m)}(n_1,n_2)$ are the prediction error fields of 1st, 2nd, 3rd and 4th quadrature plane prediction error fields of the mth lattice stage. $x(n_1,n_2)$ defines 2D input data.

2D transfer functions of quadrature plain filters can be defined in the terms of lattice coefficients. (m+1)th stage coefficient matrix for 2D transfer function is:

$$B_{00}^{(m+1)} = \hat{B}_{00}^{(m+1)} - k_1^{(m+1)} \hat{B}_{10}^{(m+1)} - k_2^{(m+1)} \hat{B}_{11}^{(m+1)} \; k_3^{(m+1)} \hat{B}_{01}^{(m+1)} \quad (3)$$

where $B_{00}^{(m+1)}$ is coefficient matrix related with forward prediction error filter and $B_{10}^{(m+1)}$, $B_{11}^{(m+1)}$ and $B_{01}^{(m+1)}$ are coefficient matrixes related with backward prediction error filters [10]. Transfer functions of forward and backward prediction error filters are below:

$$H_{00}^{(m+1)}(z_1,z_2) = \sum_{j=0}^{m+1}\sum_{l=0}^{m+1} b_{00}^{(m+1)}(j,l) z_1^{-1} z_2^{-1} \quad (4.a)$$

$$H_{10}^{(m+1)}(z_1,z_2) = z_1^{-(m+1)} H_{00}^{(m+1)}(z_1^{-1},z_2) \quad (4.b)$$

$$H_{11}^{(m+1)}(z_1,z_2) = z_1^{-(m+1)} z_2^{-(m+1)} H_{00}^{(m+1)}(z_1^{-1},z_2^{-1}) \quad (4.c)$$

$$H_{01}^{(m+1)}(z_1,z_2) = z_2^{-(m+1)} H_{00}^{(m+1)}(z_1,z_2^{-1}) \quad (4.d)$$

Additional and more detailed information about 4 channel filter bank design can be found in [11].

3. LATTICE FILTERS BASED SPECKLE REDUCTION

3.1 Wavelet Transform Based Speckle Noise Reduction

There are lots of approaches in speckle noise reduction since speckle noise reduction in SAR imaging without blurring the edges is an important problem. Especially wavelet based techniques are widely used in speckle noise reduction. In wavelet based denoising methods, the speckled image is decomposed into subband images using discrete or stationary wavelet transforms, then hard or soft thresholding methods are applied on the these subband images which correspond to wavelet approximation or detail coefficients. Below is the most widely used soft thresholding equation [12]:

$$T_s(Y,\delta) = \begin{cases} \mathrm{sgn}(Y)(|Y| - \delta, & |Y| \geq \delta \\ 0, & |Y| < \delta \end{cases} \quad (5)$$

Threshold δ is estimated by using Y wavelet coefficients. There is a simple equatition in order to estimate δ threshold:

$$\delta_{h,I}(e) = f_Z \sigma_{h,I} = f_a \sqrt{\frac{1}{N-1}\sum (C_{h,I} - m)^2} \quad (6)$$

where N is image data number, m is the mean of the $C_{h,I}$ wavelet coefficients and I is decomposition level and f_a a is sistematically $\frac{1}{I}$ determined threshold factor [12].

After applying thresholding on the subband images the denoised image is obtained by applying the inverse wavelet transforms on these thresholded subband images.

3.2 Lattice Filter Based Speckle Noise Reduction

Every error field of the 2-D lattice filter is arranged as to be equal to a subband of 4 channel filter bank by making appropriate changes on these error fields. LL, HL, HH and LH subband images are equal to subbands in the Figure 1, respectively. 2-D lattice filters whose transfer functions are arranged to create these 4 subbands can be separate to 4 filters. Simply, when one of these filters is defined in terms of lattice parameters the other filters can be obtained from this filter with appropriate latencies [11].

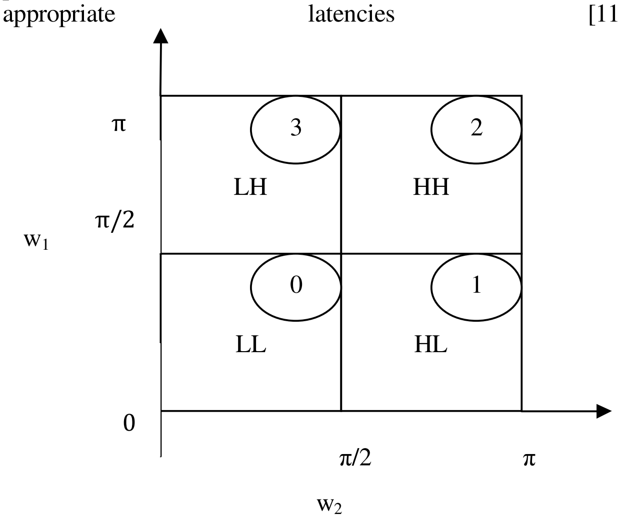


Figure1 – 4 Bands of 2-D Spectrum

$$H_1(z_1,z_2) = z_1^{-1} H_0(-z_1^{-1}, z_2) \quad (7.a)$$

$$H_2(z_1,z_2) = z_1^{-1} z_2^{-1} H_0(-z_1^{-1}, -z_2^{-1}) \quad (7.b)$$

$$H_3(z_1,z_2) = z_2^{-1} H_0(z_1, -z_2^{-1}) \quad (7.c)$$

The error fields are obtained starting from 0^{th} stage filter as below:

$$X_0^0(z_1,z_2)=X_1^0(z_1,z_2)=X_2^0(z_1,z_2)=X_3^0(z_1,z_2)=X(z_1,z_2) \quad (8)$$

$H_0(z_1,z_2)$ can be defined in terms of lattice parameters as:

$$H_0^{(1)}(z_1,z_2)=1-k_1^{(1)}z_1^{-1}-k_2^{(1)}z_1^{-1}z_2^{-1}-k_3^{(1)}z_2^{-1} \quad (9)$$

Input-output equation of analysis lattice filter is given as [11]:

$$\begin{bmatrix} X_0^{(m+1)}(z_1,z_2) \\ X_1^{(m+1)}(z_1,z_2) \\ X_2^{(m+1)}(z_1,z_2) \\ X_3^{(m+1)}(z_1,z_2) \end{bmatrix} = \begin{bmatrix} 1 & -k_1^{(m+1)} & -k_2^{(m+1)} & -k_3^{(m+1)} \\ k_1^{(m+1)} & 1 & -k_3^{(m+1)} & k_2^{(m+1)} \\ -k_2^{(m+1)} & k_3^{(m+1)} & 1 & k_1^{(m+1)} \\ k_3^{(m+1)} & k_2^{(m+1)} & -k_1^{(m+1)} & 1 \end{bmatrix} x \begin{bmatrix} X_0^{(m)}(z_1,z_2) \\ z_1^{-1}X_1^{(m)}(z_1,z_2) \\ z_1^{-1}z_2^{-1}X_2^{(m)}(z_1,z_2) \\ z_2^{-1}X_3^{(m)}(z_1,z_2) \end{bmatrix} \quad (10)$$

where m=0,1,2,……..,M-1 and $X_0^{(m+1)}(z_1,z_2)$, $X_1^{(m+1)}(z_1,z_2)$, $X_2^{(m+1)}(z_1,z_2)$ and $X_3^{(m+1)}(z_1,z_2)$ are (m+1)th level lattice filter outputs and they correspond to LL, LH, HL and HH subband images.

Using the optimization algorithm developed in [11] the lattice coefficients are determined so as to minimize the stop band energy in the frequency domain. Although analysis lattice filter has 4 filters for every stage, it is enough to consider only one since they are shifted versions of each other. If we choose $H_0(m+1)$ as LL filter, target will be to minimize the energy out of the 0^{th} area shown in the Figure 1.

$$\Phi^{(2m+1)} = \iint_{(w_1,w_2)\in R_1^{'}} \left| H_0^{(2m+1)}(e^{jw1},e^{jw2}) \right|^2 dw_1 dw_2 \quad (11)$$

where $R_0^{'}=\{0\le(w_1,w_2)\le\pi,(w_1,w_2)\notin R_0\}$.

Transfer function of (2m+1)th stage filter above can be written in terms of (2m-1)th stage filter.

For 1^{st} stage;

$$H_0^{(1)}(e^{jw_1},e^{jw_2})=\frac{1}{\delta^{(1)}}\left[1-k_1^{(1)}e^{-jw_1}-k_2^{(1)}e^{-jw_1}e^{-jw_2}-k_3^{(1)}e^{-jw_2}\right] (12)$$

with initial conditions:

$$H_0^{(0)}(e^{jw_1},e^{jw_2})=H_1^{(0)}(e^{jw_1},e^{jw_2})=H_2^{(0)}(e^{jw_1},e^{jw_2})=H_3^{(0)}(e^{jw_1},e^{jw_2})=1 \quad (13)$$

Lattice coefficients can be calculated by equalizing gradient of target function due to lattice coefficients to zero.

The use of lattice structure yields the combination of 4 analysis subband filters into a single structure in the type of lattice and one can obtain high level filter banks using hierarchical feature of lattice structures easily.

The proposed speckle reduction algorithm may be summarized as follows:

Step 1: The speckled image is decomposed into subbands using 2-D lattice filter. Lattice parameters and lattice stages are chosen suitable according to the situation.

Step 2: As similar to wavelet based speckle noise reduction method a threshold value is estimated according to noise variance in each detail subband and soft-thresholding is applied by using the equations 5 and 6.

Step 3: The despeckled image is obtained from the thresholded subband images using the inverse lattice filter.

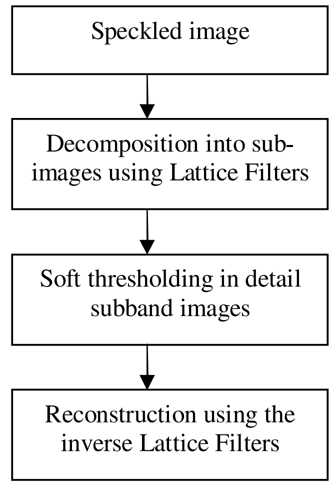


Figure2 – Flow-chart for the proposed speckle reduction method

4. RESULTS

The proposed speckle reduction method is applied to several test images corrupted by speckle noise as well as experimental RADARSAT/SAR images. The performance of the proposed method has also been compared with median filtering and stationary wavelet transform based speckle reduction methods by calculating PSNR (Peak Signal to Noise Ratio). Results can be seen in Table 1, Table 2 and Table 3 for different test images. PSNR and MSE are given as:

$$PSNR = 10\log_{10}\left[\frac{255^2}{MSE}\right] dB \quad (14)$$

$$MSE = \frac{1}{K}\sum_{i=1}^{K}(X-P)^2 \quad (15)$$

where X is original image, P is noisy image and K is the dimension of the image.

Figure 3 a, b, c, d, e and Figure 4 a, b, c, d shows the speckled image and despeckled images using median filtering, stationary wavelet transform and proposed methods, respectively. Figures show that 2-D lattice filter based speckle noise reduction technique is very successful in speckle noise reduction. And also when it is compared with the other successful methods it may be used efficiently for speckle noise reductions in SAR images and may be an alternative to the other widely used methods.

5. CONCLUSIONS

In this work, a new speckle reduction method which uses 2-D lattice filters based subband decomposition is presented. The performance of the proposed method has also been compared with median filtering, and stationary wavelet transform based speckle reduction methods. Although wavelet transform, especially Stationary Wavelet Transform, has an important place in successful speckle noise reduction methods, the proposed lattice filters based method is an important alternative because of its simplicity and reduce complexity compared to the widely used wavelet transform based methods. In addition the proposed lattice filters based method works faster than wavelet transform based speckle reduction methods and has a structure which is applicable to every type of images. Results also show that the proposed method may be an alternative to the widely used wavelet transform based methods for speckle noise reduction in SAR images.

REFERENCES

[1] J.S.Lim,1990. *Two Dimensional Signal and Image processing*, Prentice-Hall, Englewood Cliffs, NJ, 469-476.

[2] J.S. Lee, 1986. "Speckle suppression and analysis for synthetic aperture radar images", *Opt. Eng*, 25 (5), 636-643.

[3] H.H. Arsenault, M. Levesque,1984. "Combined homomorhic and local-statistics processing for restoration of images degraded by signal dependent noise". *APPL. OPT.*.23(6), 845-850.

[4] D.L. Donoho,1995. "Denoising by soft thresholding",. *IEEE Trans. Inform. Theory*, 41(3), 613-627.

[5] J. Zhang, X. Cheng, J. Liu ,1998. "A speckle reduction algorithm by softthresholding based on wavelet filters for SAR images", *Proceedings of the 4th Int. Conf. on Signal Processing*, 1469-1472..

[6] M. Sezgin, I. Erer ve O. K. Ersoy, "DFT/RDFT Filter Bank Approach to Speckle Reduction in SAR Images ", *the IEEE Geoscience and Remote Sensing Symposium, IGARSS2005,* 25-29 July 2005, Seoul, Korea

[7] P.P. Vaidyanathan, P.Q. Hoang, "Lattice Structures for Optimal Design and Robust Implementation of Two-Channel Perfect Reconstruction QMF Banks", *IEEE Trans. ASSP*, Vol. 36, pp. 81-94, 1988.

[8] N. J. Fliege, *Multirate Digital Signal Processing*, John Wiley&Sons, 1994

[9] Parker, S. R. and Kayran, A. H., 1984. "Lattice Parameter Autoregressive Modelling of Two – Dimensional Fields – Part I: The Quarter Plane Case", *IEEE Transactions on Acoustics, Speech, and Signal Processing,* ASSP-32, 4.

[10] Smith M. J. T. and Barnwell, T. P., 1986. "Exact Reconstruction for Tree-Structured Subband Coders", *IEEE Transactions on ASSP,* 34.

[11] Sezen, S. And Ertüzün A., 2006, "2D Four Channel Perfect Reconstruction Filter Bank Realized with the 2D Lattice Filter Structure", S. Sezen and A. Ertüzün, *EURASIP Journal on Applied Signal Processing* 42672, 1–16.

[12] Dachasilaruk, S., Rangsanser, Y. ve Thitimahshima, P. 1999. "Application of Multiscale Edge Detection to Speckle Reduction of SAR Images", http://www.gisdevelopment.net/aars/acrs/1999/ps4/ps41055pf.htm

a) Original

b) Speckled test image

c) Median Filter

d) SWT

e) Proposed Method

Figure 3 – a) Original b) speckled test image ,despeckled images using c) median filtering, d) SWT-based method, e) Lattice filters based method.

NOISE VARIANCE	Median Filter	Stationary Wavelet Transform (SWT)	Proposed Method (2-D Lattice Filter)
0.04	23.6519	24.1259	25.9553
0.08	20.7930	21.9089	22.4732
0.12	19.3533	20.7559	21.0734

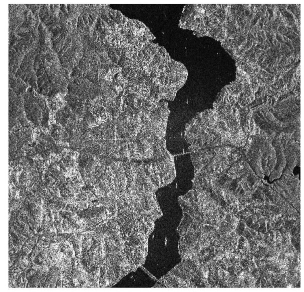
Table 1 – PSNR results (in dB) for despeckled Cameraman test images with different methods

NOISE VARIANCE	Median Filter	Stationary Wavelet Transform (SWT)	Proposed Method (2-D Lattice Filter)
0.04	24.1256	25.0390	25.6706
0.08	21.5684	22.3985	22.7913
0.12	19.9860	20.8555	21.0303

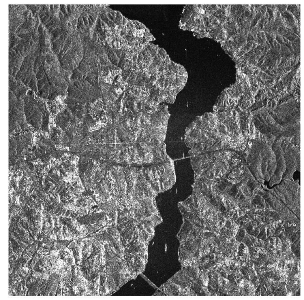
Table 2 – PSNR results (in dB) for despeckled Peppers test images with different methods

NOISE VARIANCE	Median Filter	Stationary Wavelet Transform (SWT)	Proposed Method (2-D Lattice Filter)
0.04	23.8716	24.8205	25.4676
0.08	20.9846	22.0024	22.3820
0.12	19.4875	20.3915	20.8247

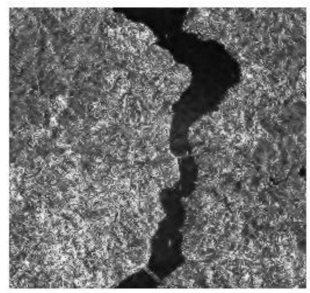
Table 3 – PSNR results (in dB) for despeckled Lena test images with different methods



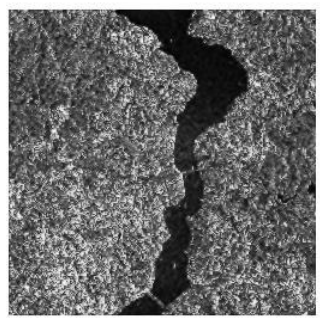
a) Original



b) Median Filter



c) SWT



d) Proposed Method

Figure 4 – a) original ,despeckled images using b) median filtering, c) SWT-based method, d) Lattice filters based method.