Performance Measure of Despeckling of SAR Image using Multiwavelets

Jawed Qumar
Ex Defense Scientist
Motorola India Bangalore
Email: Jawed.qumar@gmail.com

Sumana Gupta
Department of Electrical Engineering
Indian Institute of Technology Kanpur
Email: sumana@iitk.ac.in

***Abstract*— Synthetic aperture radars (SAR) are coherent imaging systems that produce complex-valued images of the ground. SAR images are corrupted by multiplicative noise (speckle Noise). It is due to coherent processing where multiscatterers present in a resolution cell. The presence of speckle in an image reduces the resolution of the image and the detectability of the target. The Multiwavelet transformations are useful for speckle reduction through its sub-band images. The speckle noise variances are estimated first using which donoho thereshold is computed. Then transform coefficients are pruned to reduce the speckle noise.**

The proposed method shows great promise to reduce the speckle noise and evaluates the performance measure for different Multiwavelets. In this paper several thresholding scheme are used with different Multiwavelets and Prefilters.

I. Introduction

In the last two decades great improvements have been made in SAR technology. It uses a coherent microwave sensor that can penetrate foliage and clouds and operate day or night because it provides its own illumination. An image is computed after the SAR system receives the coherent sum of reflected monochromatic microwaves. When the airborne antenna moves, the phase of each elementary signal is modified according to the distance between the target and antenna. The resulting signal is complex [1], with a phase uniformly distributed on [0, 2π] and a magnitude having large random variations. These produce strong granulation in image termed as speckle.

The speckle noise complicates in interpretation of the image since it obscures the scene content of the image, the effectiveness of image segmentation and other information extraction. Speckle reduction is a necessary procedure before efficient class discrimination can be performed. The speckle noise can typically be modelled as gamma distributed which is the combination of chi-square and exponential distribution. Logarithmic transformation of a SAR image converts the multiplicative noise model to additive noise model.

The most well-known and widely used image-domain speckle filter is the local statistics adaptive filter proposed by Lee [2], which uses local statistics such as mean and standard deviation on fixed-size window to determine the degree of smoothing. Although the Lee filter can preserve steep edges, the loss of fine details and the degradation of spatial resolution may occur by using too large a window. But on the other side the use of small window implies less suppression of speckle noise in homogeneous area.The theory of adaptive window solve the problem to some extent [3].

Incoherently averaging several frames obtained from a portion of the available azimuth spectral bandwidth, this is the base of multi-look SAR (spot-light mode) processing. The Doppler frequency spectrum is divided into N segments, then each segment is processed separately to form either an intensity or an amplitude SAR image, and the N images are summed together to form a N-look SAR image. This process reduces the noise variance by a factor of $\sqrt{N}$, but it also degrades the spatial resolution by a factor of N.

In this paper we use multiwavelets to despeckle the SAR. A motivation for studying multiwavelets is the fact that it can have simultaneously short support, orthogonality, symmetry and high number of vanishing moments.

In this paper we provide a brief theory of multiwavelets in section 2, and describe purposed method for despeckling in section 3. The quantitative performance measure of different multiwavelets is discussed in section 4. We conclude the paper in section 5.

II. Discrete Multiwavelet Transform

In DWT, integer translation $\phi(t)$ $\phi(t-k)$ construct a subspace V_0. A subspace V_j is generated by using $\phi(2^j t - k)$, j $\in$ Z such that,

$$\ldots V_{-1} \subset V_0 \subset V_1 \subset \ldots \subset V_j \ldots$$

$$\bigcup_{-\infty}^{j=\infty} V_j = L^2(R), \bigcap_{-\infty}^{j=\infty} V_j = 0$$

A mother wavelet $\psi(t)$ is defined to extract the high frequency information. The subspace generated by $\psi(2^j t - k)$, is called W_j. That is

$$V_{j+1} = W_j \oplus V_j$$

Therefore

$$V_{j+1} = W_j \oplus W_{j-1} \oplus \ldots \oplus V_1$$

However there is limit to the time-frequency localization of a single wavelet [4]. Multiwavelets are the extension of wavelets. Wavelets have an associated scaling function $\phi(t)$ and wavelet function $\psi(t)$ while multiwavelets have two or more scaling and wavelet functions. For notational convenience the set of scaling functions can be written using the vector notation $\Phi(t) \equiv [\ \phi_1(t)\ \phi_2(t)\ \ldots\ \phi_r(t)\ ]$ where $\Phi(t)$ is called the multiscaling function. Likewise the multiwavelet function is defined from the set of wavelet functions as $\Psi(t) \equiv [\ \psi_1(t)\ \psi_2(t)\ \ldots\ \psi_r(t)\ ]$. When $r = 1$, $\Psi(t)$ is called a scalar wavelet, or simply wavelet. While in principle r can be arbitrarily large, the multiwavelets studied to date are primarily for $r = 2$.

The multiwavelet two-scale equations resemble those for scalar wavelets

$$\Phi(t) = \sqrt{2} \sum_{k=0}^{m-1} \mathbf{G}_k \Phi(2t-k)$$

$$\Psi(t) = \sqrt{2} \sum_{k=0}^{m-1} \mathbf{H}_k \Phi(2t-k),$$

Here $\{\mathbf{G}_k\}$ and $\{\mathbf{H}_k\}$ are matrix filters, i.e $\mathbf{H}_k$ and $\mathbf{G}_k$ are $r \times r$ low-pass and High-pass matrices respectively for each integer k. The matrix elements in these filters provide more degrees of freedom than a traditional scalar wavelet. These extra degrees of freedom can be used to incorporate useful properties such as orthogonality, symmetry, and high order of approximation, Which are known to be important for image processing. The key then is to find out how to make the best use of these extra degrees of freedom. Using Fractal interpolation Geronimo, Hardin, and Massopust (GHM)[5] succeeded to construct multi-scaling function $\phi_1(t)$ and $\phi_2(t)$ as shown in Fig.1, and two mother wavelet functions $\psi_1(t)$ and $\psi_2(t)$, shown in Fig.2 where $r = 2$ and $m = 4$. The dilation and translation equations for this system have four coefficients:

$$\mathbf{G}_0 = \begin{pmatrix} \frac{3}{5} & \frac{4\sqrt{2}}{5} \\ \frac{-1}{10\sqrt{2}} & \frac{-3}{10} \end{pmatrix} \quad \mathbf{G}_1 = \begin{pmatrix} \frac{3}{5} & 0 \\ \frac{9}{10\sqrt{2}} & 1 \end{pmatrix}$$

$$\mathbf{G}_2 = \begin{pmatrix} 0 & 0 \\ \frac{9}{10\sqrt{2}} & \frac{-3}{10} \end{pmatrix} \quad \mathbf{G}_3 = \begin{pmatrix} 0 & 0 \\ \frac{-1}{\sqrt{2}} & 0 \end{pmatrix}$$

$$\mathbf{H}_0 = \frac{1}{10} \begin{pmatrix} \frac{-1}{\sqrt{2}} & -3 \\ 1 & 3\sqrt{2} \end{pmatrix} \quad \mathbf{H}_1 = \frac{1}{10} \begin{pmatrix} \frac{9}{\sqrt{2}} & 10 \\ -9 & 0 \end{pmatrix}$$

$$\mathbf{H}_2 = \frac{1}{10} \begin{pmatrix} \frac{9}{\sqrt{2}} & -3 \\ 9 & -3\sqrt{2} \end{pmatrix} \quad \mathbf{H}_3 = \frac{1}{10} \begin{pmatrix} \frac{-1}{\sqrt{2}} & 0 \\ -1 & 0 \end{pmatrix}$$

The GHM multiwavelet has several remarkable properties. Both scaling functions have short supports $[0,1]$ and $[0,2]$ respectively, are symmetric and system has second order of approximation and multiwavelets form symmetric/antisymmetric pair. Translates of scaling function and wavelets are orthogonal. This is not possible for single wavelet.

The application of multiwavelets require that the input signal first be vectorized which is called preprocessing and better known as multiwavelet initialization[6] or prefiltering. Here

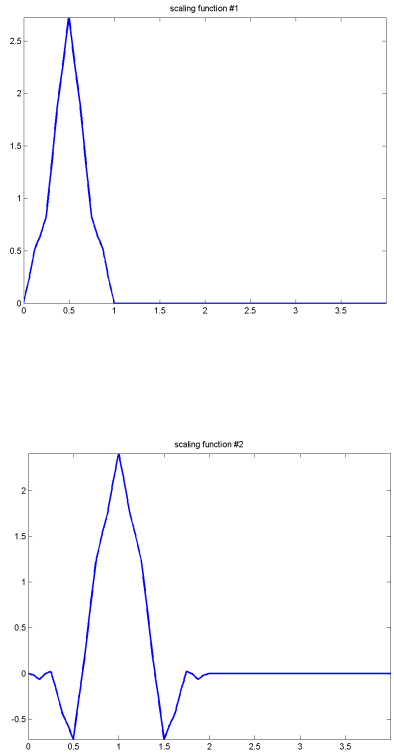

Fig. 1. GHM Pair of Scaling Functions $\phi_1(t)$ and $\phi_2(t)$

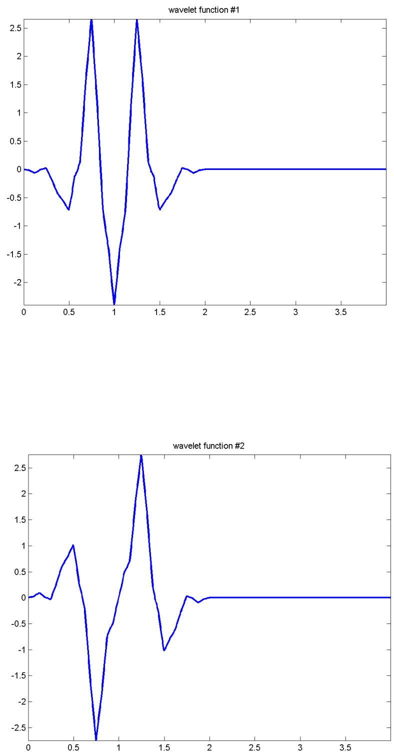

Fig. 2. GHM Pair of Multiwavelets Functions $\psi_1(t)$ and $\psi_2(t)$

L_1L_1	L_2L_1	H_1L_1	H_2L_1
L_1L_2	L_2L_2	H_1L_2	H_2L_2
L_1H_1	L_2H_1	H_1H_1	H_2H_1
L_1H_2	L_2H_2	H_1H_2	H_1H_2

Fig. 3. Result of one level 2D-DMWT decomposition

prefiltering has been done by algorithm given by Strela[7].The prefilter output maintains the critical representation i.e if the image input to prefilter of size $M \times N$, then there will be four filtered output subimages of size $(M \times N)/4$. The boundary level of the image is assumed periodically extended for filtering as given by Strang [8]. The theory of multiwavelets is also based on the idea of Multiresolution Analysis (MRA) [4], just like the scalar wavelet. The difference between them is that, multiwavelets have r scaling functions. During a single level of decomposition using scalar wavelet transform the image is replaced with four blocks corresponding to the subbands, representing either low-pass or high-pass in each direction. Here in case of GHM or Chui and Lian [9] multiwavelets have two channels $(r = 2)$, so that there will be two sets of scaling coefficient and two set of wavelet coefficients. Each 2D-DMWT decomposition step results in 16 subimages containing multiwavelet coefficients related to lowpass and highpass filters shown as in Fig.3 Multiwavelet decomposition iterates on the low-pass coefficients from the previous decomposition, the quarter image of low-pass coefficients is actually a 2×2 subband $L_1L_1, L_2L_1, L_1L_2$and L_2L_2 The next step decomposes the low-low pass subband matrix in the similar way. No prefilter is performed for these later decomposition. An N-level decomposition of a 2-D image will produce 4(3N +1) subimages. Multiwavelets system can simultaneously provide perfect reconstruction while preserving length (orthogonality), good performance at the boundaries (linear phase symmetry), and a high order of approximation (vanishing moment).

III. Despeckling of SAR images

Here we first logarithmically transform the SAR image so that the multiplicative noise (speckle noise) is approximated as additive noise. First prefiltering of logarithmically transformed gray level (or intensity) of image with suitable prefilter depending on what multiwavelets are used like GHM, CL, Sa4 [10], Bih34 [11] and Cardbal4 [12] are computed. Then decomposition of preprocessed image at different levels is computed. Preprocessed image gets decomposed into sixteen bands at each level. Low band contains approximation $(L_1L_1, L_1L_2, L_2L_1andL_2L_2)$ while the other bands consist detail information $(L_iH_j, H_iL_jandH_iH_j$i,j = 1,2). The noise variance σ^2 in transformed coefficient is not known. This has to be estimated first. In this case standard deviation σ is estimated as the median absolute deviation of the diagonal detail coefficients on $H_iH_j\ i,j = 1,2$.

$$\sigma = Median(|W_{ij})|/0.6745, W_{ij} \in subbandH_iH_j$$

$$T = \gamma\sigma\sqrt{2ln(n)/n}$$

where γ is a constant. Here γ is taken mean of multiwavelet coeffcients at the final level of decomposition. n is the number of sample data. The thresholding of the subband coefficients is taken according to the following method.
a) Scalar way of thresholding: There are two ways to apply the threshold.

Soft thresholding:The function is defined as

$$H(x) = \begin{cases} x - T & \text{for } x > T \\ 0 & \text{for } |x| \leq T \\ x + T & \text{for } x < -T \end{cases}$$

Hard theresholding: The function is defined as

$$H(x) = \begin{cases} x & \text{for } x > T \\ 0 & \text{for } |x| \leq T \\ -x & \text{for } x < -T \end{cases}$$

b) Vector thresholding with decorrelation : In this we perform vector thresholding with decorrelation matrix of 2D multiwavelet transform coefficient [13]. Here scaling coefficients remains untouched. After decorrelated the DMWT coefficients we apply soft and hard threshold to get the significant coefficients.
Once the Transform coefficients are thresholded, then speckle reduced image is obtained by synthesis part of DMWT coefficients. The performance of speckle reduction quantitively is evaluated in terms of Root mean square error (RMSE). RMSE is computed for different multiwavelets with different possible prefilter.

IV. Simulation Study And Discussion

The despeckling method described in previous section is applied in experiment to a SAR image with size 512×512 gray level. All the multiwavelets applied here for despeckling have two vanishing moments. The multiwavelets are used with repeated row (rr) and approximation prefilter (AP). In addition the GHM multiwavelet can also be used with orthogonal approximation prefilter (ORAP)[14]. For all cases, a five level decomposition is used. In order to obtain the speckled noisy image, gamma distributed speckle noise is generated with variance 0.04 and mixed with SAR image. The results are shown with GHM multiwavelet with repeated row (rr) preprocessing. Original SAR image is shown Fig4. Image with speckle noise with variance 0.04 is shown in Fig5. The despeckled image with scalar soft thresholding is shown in Fig 6. GHM multiwavelet with repeated row gives the best result with scalar soft thresholding. Despeckling with scalar hard and vector hard thresholding are shown in Fig 6. and Fig 7 respectively. In Table I the type of multiwavelets, the

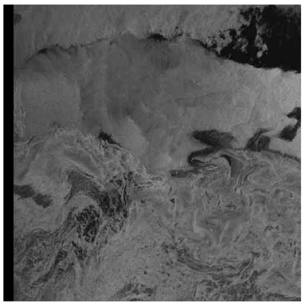

Fig. 4. Original Image

Fig. 5. Speckled Image (σ^2 = 0.04)

type of prefilter and type of thresholding method are given. The results reveal Chui-Lian (CL) multiwavelet gives the best performance with repeated row preprocessing with scalar hard and vector hard thresholding. The performances of the multiwavelets which are not good with scalar soft threshold, are improved with the use of other methods.

V. Conclusion

In this paper we despeckled the SAR image with different multiwavlets and with different prefilters. Performance are measured with root mean square error (RMSE) comparison in dB, of despeckled image and original image.

Fig. 7. Despeckled Image Hard thresholding

TABLE I

RMSE with different Multiwavelet and Prefilter

MW	Preflt	scalar(sof)	scalar(har)	vector(har)
ghm	ghmap	9.2715	8.8066	9.1502
ghm	rr	**8.4401**	8.8066	8.6974
ghm	ghmorap	10.1045	8.9168	9.8909
cl	clap	10.3242	9.2655	8.9653
cl	rr	8.4445	**8.3201**	**7.8533**
sa4	sa4ap	9.3122	8.9980	8.7822

Acknowledgment

The authors would like to thank to Defense Research and development organization of India to allow to work in this area and arranging all the required facility, and also like to thank their friends for helping in giving valuable suggestion.

References

[1] LEE,J.S and Jurkevich,I. *Speckle Filtering of Synthetic aperture radar images A review*, Remote sensing Reiews 8, pp.313-340, 1994

[2] LEE,J.S. *Speckle analysis and smoothing of Synthetic aperture radar images*, Computer Graph. Image Process, Vol, 17, pp.24-31, 1981

[3] Park,J.M Song,W.J and Pearlman,W.A.*Speckle Filtering of SAR images based on adaptive windowing*, IEE-proc. Image Signal Process, Vol 146, No. 4, pp 191-197, August. 1999.

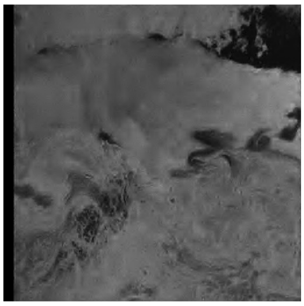

Fig. 6. Despeckled Image Soft thresholding

Fig. 8. Despeckled Image Vector(Hard) thresholding

[4] S.Mallat, *A theory for Multiresolution signal decomposition. The wavelet representation*, IEEE Transaction on Pattern Analysis Machine Intelligence, vol. 11, pp. 674-693, July 1989
[5] Xia,X.G., Geronimo, J.S., Hardin, D.P., and Suter, B.W." Design of prefilters for discrete multiwavelet transform". *IEEE Trans Signal Process*, 1996, 44, (1), pp.25-35
[6] Xia,X.G., Geronimo, J.S., Hardin, D.P., and Suter, B.W." Design of prefilters for discrete multiwavelet transform". *IEEE Trans Signal Process*, 1996, 44, (1), pp.25-35
[7] Strela,V." Multiwavelet: Theory and Applicattion". Phd dissertation, Department of Mathematics, Massachusetts of Technology,1996
[8] Strang,G. and Nguyen,T." Wavelets and Filter Banks". Wellesley-Cambridge Press
[9] Chui,C.K and Lian,J. " A study of orthonormal multi-wavelets", Ctr. for Approximation Theory, Texas A and M Univ., College Station, Tech. Report. 351, 1995.
[10] L.-X. Shen, H. H. Tan, and J. Y. Tham, "Symmetric-antisymmetric orthonormal multiwavelets and related scalar wavelets", preprint (1997)
[11] V. Strela, "A note on Construction of biorthogonal multi-scaling functions", in Contemporary Mathematics, A. Aldroubi and E. B. Lin (eds.), AMS (1998) 149-157
[12] I. Selesnick, "Cardinal Multiwavelets and the Sampling Theorem",preprint (1998)
[13] Downie,T.R and Silverman, *The Discrete Multiple wavelet Transform and Thresholding Methods*,IEEE Transaction on Signal Procc, vol - 46, No.9 1998
[14] Hardin,D.P. and Roach,D.W.*Multiwavelet prefilters I: Orthogonal Prefilters Preserving Approximation Order p¡ - 2*, http://citeseer.nj.nec.com/cs.