IEEE Sponsored International Conference on Advances in computer Vision and Information Technology (IEEE-ACVIT-07)28th-30th November-2007 Aurangabad-India PP1400-1405 ISBN 978-81-898866-74-7©2007

SPECKLE NOISE REDUCTION OF SYNTHETIC APERTURE RADAR (SAR) IMAGE USING MULTI-RESOLUTION TECHNIQUE

Ganesh Magar[#], S. S. Gornale[*], Vikas Humbe[#], Pravin Yannawar[#], Ramesh Manza[#], K.V. Kale[#]

[#]Dept. of Computer Science and Information Technology, Dr. Babasaheb Ambedkar Marathwada University, Aurangabad, (MS) - 431004 India

[*]Department of Computer Science, University of Pune, Pune (MS)-India

(ganeshmagar@hotmail.com, shivanand_gornale@yahoo.com)

ABSTRACT

Synthetic Aperture Radar (SAR) images are contaminated by multiplicative speckle noise, a chaotic phenomenon that results from coherent energy imaging; and that obscures the scene complex and strongly reduces the possibility to observe objects. Multiplicative speckle noise limits the classical coder/decoder algorithm in spatial domain. Various scalar wavelet based techniques so far developed for removal various noise but; these wavelet transforms cannot posses all desirable features simultaneously. Relatively new class of wavelets called Multiwavelet; are new addition to the body of wavelet theory. Realizable as matrix –valued filter banks leading to wavelet basis, were introduced and which are able to posses all desirable properties simultaneously and overcomes the limitations of scalar wavelets. In this paper, we proposed a de-noising scheme of speckle noise removal within the Multiwavelet framework. Newly proposed method achieves favorable PSNR and performs superior speckle noise reduction.

KEY WORDS

Synthetic Aperture Radar (SAR), Multiplicative Speckle Noise, Multi-resolution technique

1. Introduction

Synthetic aperture radar (SAR) is a remote sensing technology that uses the motion of the radar transmitter to synthesize an antenna aperture much larger than the actual antenna aperture in order to yield high spatial resolution radar images. In the last few years, high-quality images of the earth produced by SAR systems, carried on a variety of airborne and space borne platforms, have become increasingly available. A major problem with use of SAR imagery is a kind of signal dependent noise: the speckle noise i.e. consequences image formation under coherent radiation [1, 2, 3]. Since speckle damages radiometric resolution and affects human interpretation and scene analysis. It is generally desirable that image brightness is to be uniform except where it changes to form an image. There is a variation in the brightness of a displayed image even when no image detail is present. This variation is usually random and has no particular pattern reducing the image quality specifically when the images are small and have relatively low contrast. This random variation in image brightness is nothing but a noise. All SAR images contain multiplicative speckle noise [4-6] .The presence of noise gives an image a grainy, textured, or snowy appearance. No imaging method is free of noise.

Many authors have developed SAR image de-nosing methods mostly focus on using wavelet transform for its multiresolution decomposition allowing efficient image analysis and noise reduction. Recent developed Multiwavelet can posse's compact support, orthogonality, symmetric, and high order vanish moments simultaneously which desirable properties for best performance in image are de-noising while scalar wavelet lack of it. Thus Multiwavelet offers the possibility of superior performance in obviating some of the limitations of scalar wavelets [7-8]. In this work we explore an algorithm using soft thresholding speckle noise reduction with various decomposition and reconstruction filters with different pre-processing filters.

2. Multi-resolution Technique:

Wavelet (Multi-resolution analysis) is a useful transform tool for signal processing applications such as image compression and de-noising. Wavelets are generated by one scaling function, so called scalar wavelets too. In comparison to scalar wavelets, Multiwavelet have several advantages such as short support, orthogonality, symmetry, and vanishing moments.[9-11]

Multiwavelet can simultaneously provide perfect reconstruction while preserving length (orthogonality), good performance at the boundaries (via linear-phase symmetry) and a high order of approximation (vanishing moments).

Multiwavelets are characterized with several scaling functions and associated wavelet functions. Let the scaling functions be denoted in vector form as Φ(t) = [Φ1(t), Φ2(t), . . . , Φr(t)]T, where Φ(t) is called the multiscaling function, T denotes the vector transpose and Φj(t) is the jth scaling function. Likewise, let the wavelets be denoted as Ψ(t) = [ψ1(t), ψ2(t), . . . , ψr(t)] T, where ψj(t) is the jth wavelet function. Then, the dilation and wavelet equations for Multiwavelet take the following forms, respectively:

$$\phi(\mathrm{t}) = \sum_{k}^{r} \mathrm{H}_k \ \phi(2\mathrm{t} - \mathrm{k}),$$

$$\psi(\mathrm{t}) = \sum_{k}^{r} \mathrm{G}_k \ \phi(2\mathrm{t} - \mathrm{k}) \qquad (1)$$

Multiwavelet bases of multiplicity r provide a multi-resolution analysis is $\{V_n\}_{n \in Z}$ of L2 (R) using the Multiwavelet function Ψ(t) and multiscaling function Φ(t).

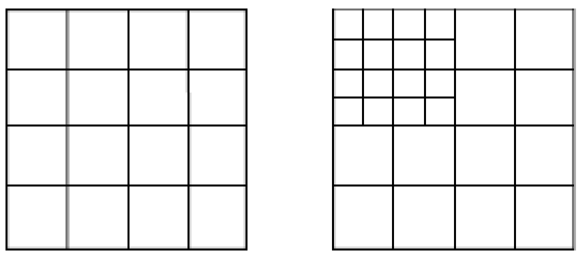
The jth scaling space is given by

$$V_j = \overline{span\{2^{j/2}\phi_i(2^j \cdot t - k) : 1 \le i \le r, k \in Z\}} \quad 2$$

The jth wavelet space is given by

$$W_j = \overline{span\{2^{j/2}\psi_i(2^j \cdot t - k) : 1 \le i \le r, k \in Z\}} \quad 3$$

Where VJ ⊥ Wj. The multiscaling function satisfied the above r-scale equation (1). Where Hk and Gk are r x r matrix coefficients of low pass multifilters and high pass multifilters. The low pass filters H and the high pass filter G is r x r matrix filters, instead of scalars. In theory, r could be as large as possible, but in practice it is usually chosen to be two i.e r =2 [12-16].
The Multiwavelet used here have two channels, so there will be two sets of scaling coefficients and two sets of wavelet coefficients. Thus the two-dimensional image data after one level Multiwavelet decomposition are replaced by sixteen blocks corresponding to the subbands as shown in Fig.1 (a). The sixteen blocks represent either low pass or high pass filtering in each direction, not four blocks in scalar wavelet decomposition. For two-level Multiwavelet decomposition, the four low frequency subbands are decomposed into sixteen blocks again as shown in Fig.1(a) and (b).



(a) (b)

Figure 1: (a) Illustration of one-level Multiwavelet decomposition.

3. Multiwavelet based Image De-noising

Synthetic Aperture Radar images are usually corrupted by speckle noise. There are various techniques available for de-noising the signal and images. Wavelet thresholding is an effective method of de-noising noisy signals; which plays an important role in de-noising the image and it is treated as widely investigated noise reduction method [17-20]. The wavelet de-noising is achieved via thresholding or shrinkage. Wavelet thresholding procedure removes noise by thresholding only the wavelet coefficient of the details coefficients, by keeping the low-resolution coefficients unaltered. There are two thresholding methods frequently used soft thresholding and hard thresholding. A procedure of keep or kill is called hard thresholding and alternative to this procedure is called soft thresholding. The soft thresholding is normally chosen over the hard thresholding because it yields more visually enhanced images than hard thresholding because the latter is discontinuous and yields abrupt artifacts in the recovered images, especially when the noise energy is significant. The dynamic range of synthetic aperture radar (SAR) images is higher by a factor of 5 compared to other passive remote sensing images in visible and infrared regions. More over, the speckle noise which is inherent to synthetic aperture imaging systems blurs its high frequency textural and structural information of content [20-21]. The statistical approaches for speckle suppression are found to suppress the speckle noise at the signal. The most dominant information of single frequency and single polarization SAR image are manifest in the form of local spatial variations of tone as textural and structural details [22-24]. An attempt has been made in this study to use wavelet transform for local image enhancement using a speckle filtered SAR image [24-25]. Most wavelet-based speckle noise removal approaches apply the soft-thresholding proposed by Donoho, through introducing a suitable threshold to suppress noise [3]. But during the filtering processing, edge information is also smoothed unfavorable to further image processing. By modification, this noise reduction method can keep edge and texture information at the meantime of speckle suppression.

3.2 Procedure for De-noising

The general procedure for de-noising through soft thresholding includes the following three steps.

a) Multiwavelet Decomposition
b) Threshold detail coefficients (i.e. Diagonal, Horizontal and Vertical)
c) Reconstruct.

In the above three steps, firstly the image is decomposed by the wavelet transform, secondly the detail coefficients are thresholded by the soft thresholding algorithm. After the thresholding the new detail coefficients are obtained. Using these new coefficients the image is reconstructed, which is the de-noised image by wavelet transform [3], [4], [7], [8].

4. Experimental Analysis and Interpretation.

In this experimental work we have done experiments on SAR image for removal of speckle noise using various multi-resolution techniques. We have considered ‘haar’, ‘d4’, ‘la8’, ‘bi9’, ‘bi7’, ‘ghm’, ‘cl’, ‘bih52s’,’sa4’ and ‘cardbal2’ as a decomposition and reconstruction filters with different preprocessing filters i.e. ‘bih5ap’, ‘ghmap’ and ‘sa4ap’ by keeping SNR=35; this will not affect perceptual visual quality of the image. The result are evaluated by a error visibility quality metrics MSE and PSNR at level 1 to Level 5 of decomposition for all the above decomposition and reconstruction filters with 'bih5ap' preprocessing filters at level 1 gives us good results out of that at level 1 'haar' gives promising results. We have also analyzed all the above filters from level 1 to level 5 of decomposition. Performance is good except 'bih52s' filter.

We have also analyzed all the above filters with different preprocessing filter i.e. 'ghmap' and 'sa4ap'. The same trend of the results we are getting even by changing preprocessing filters i.e. at first level all filters gives us a good result. The same evaluation criterion is followed 'haar' at level 2 gives a promising result with a 'ghmp' and 'sa4ap' preprocessing filters. Among 'haar', 'd4', 'la8', 'bi9', 'bi7', 'ghm', 'cl', 'bih52s','sa4' and 'cardbal2' Haar gives the good results at level 2 with 'bih5ap' preprocessing filter. If we increase the order and level of the wavelet filters; which leads to computational complexity and deterioration of visual quality of the de-noised image and the results are shown in table-1 and figure-1.

5. Conclusion

De-noising of SAR images through Multiwavelet techniques in image processing method has noticeable advantage over DWT. In this paper we have applied ' haar', 'd4', 'la8', 'bi9', 'bi7', 'ghm', 'cl', 'bih52s','sa4' and 'cardbal2' on SAR images at level 1 to 5 with different pre-processing filters. We have focused how the MSE and PSNR vary by selecting appropriate decomposition, reconstruction and pre-processing filters. It is observed that 'haar' gives the good results at level 1 and level 2 with 'bih5ap' preprocessing filter. If we increase the level of decomposition the computational complexity will increase. So, it is concluded that the removal of noise is depends on the type of image and type of transforms because, there is no filter that performs the best for all images. Hence, there is always necessary to select the appropriate threshold value to get perceived quality of the image with less distortion.

References:

1. Wang Wen, * Xing Fu-cheng, Dong Yun-long and Rui Guo-sheng (Department of Electronic Engineering Naval Aeronautical Engineering Academy, Yantai, 264001, China), "Speckle reduction of SAR image based on Modeling autocorrelation function of wavelet coefficients", 2005 IEEE International Symposium on Microwave, Antenna, Propagation and EMC Technologes for Wireless Communications Proceedings.
2. Xingsong Hou, Guizhong Liu, and Yiyang Zou "SAR Image Data Compression Using Wavelet PacketTransform and Universal-Trellis Coded Quantization" Ieee Transactions On Geoscience And Remote Sensing, Vol. 42, No. 11, November 2004.
3. D.L.Dohono, "De-noising by Soft Thresholding", IEEE Transactions Information Theory, No. 3, 1993, PP: 933-936.
4. S. Grace Chang, Bin Yu and M. Vattereli," Adaptive Wavelet thresholding for Image de-nosing and Compression", IEEE Transactions on Image Processing, Vol. 9, 2000, PP: 1532-1546.
5. S. Grace Chang, Bin Yu and M. Vattereli," Spatially Adaptive Wavelet thresholding with context modelling for Image de-nosing ", IEEE Transactions on Image Processing, Vol. 9,2000, PP: 1522-1530.
6. G.Panda, S.K.Meher & B.M ajhi, "Denoising of Corrupted data using Discrete Wavelet transform", Journal of the CSI Vol. 30. No.3, 2000
7. Buades A et. al, "A Review of Image De-noising Algorithms with new one", Multiscale Model, Simulation Vol 4, No. 2, 2005, PP:496-530.
8. D. Wei J. E. Odegard H. Guo M. Lang C. S. Burrus, "Simultaneous Noise Reduction and SAR Image Data Compression Using Best Wavelet Packet Basis", Proceedings of the 1995 International Conference on Image Processing (ICIP '95).
9. Andreas Reigber, "Interference Suppression in Synthesized SAR Images" IEEE Geoscience And Remote Sensing Letters, Vol. 2, No. 1, January 2005, Pp45-49.
10. Sang Huiyong, Lin Hui, Guo Huadong, and Li Xiang, "An Improved Compression Algorithm for SAR Images Using Wavelet Transform" GIS Development Proceedings,ARCS 2004.
11. J. Mvogo , G. Mercier , V.P. Onana , J.P. Rudant , E. Tonye , H. Trebossen École, "A combined Speckle noise reduction and compression of SAR images using a Multiwavelet based method to improve codec performance", IEEE International Symposium on Geoscience and Remote Sensing , Vol.1, PP: 103-105, 2001.
12. Guner Arslan and Magesh Valliappan, "Final Report on Evaluation of Synthetic Aperture Radar (SAR) Image compression Techniques", Multidimensional Signal Processing, Dec. 1998.
13. Frédéric Galland, Nicolas Bertaux, and Philippe Réfrégier, "Minimum Description Length Synthetic Aperture Radar Image Segmentation" IEEE Transactions on Image Processing, vol. 12, no. 9, september 2003,pp-995-1006.
14. Rafael C. Gonzalez and Richard E. Woods, "Digital Image Processing", 2nd edition", Prentice Hall, 2001.
15. Subhasis Saha, "Image Compression - from DCT to Wavelets: A Review", ACM Student Magzine.
16. A.K. Jain, "Fundamentals of Digital Image Processing", Upper Saddle River, NJ: Prentic Hall, 1989.

17. DuSan Gleich, Peter PlaninSiE, Bojan GergiE, Boris Banjanin, karko &Eej, "Comparison of Different Coding Schemes for SAR Image Compression", ISIE'99 - Bled, Slovenia.

18. In Kwon Kim, Rue-Hong Park, "A Fast Encoding Method Without Search For Fractal Image Compression" IEEE International Conference on Acoustics, Speech, and Signal Processing, Volume: 5, On page(s): 2625-2628, 1998.

19. James W. Owens, Michael W. Marcellin, Bobby R. Hunt, and Marvin Kleine, "Compression Of Synthetic Aperture Radar Phase History Data Using Trellis Coded Quantization Techniques", Proceedings of the 1997 International Conference on Image Processing (ICIP '97).

20. Cumming, J. Wang "Polarmetric SAR Data Compression Using Wavelet Packets in a Block Coding Scheme", IEEE International Symposium on Geoscience and Remote Sensing , Volume: 2, PP: 1126- 1128, 2002.

21. Wang Zhenhua, Xu Hondgbo, Tian Yan, Tian Jinwen, Liu Jian, "Integer Haar Wavelet for Remote Sensing Image Compression" Processing and Intelligent Control, Wuhan 430074, China, ICSP'02 Proceedings.

22. Ian Cumming and Jing Wang, "Compression of RADARSAT Data with Block Adaptive Wavelets", Proceedings of the Data Compression Conference (DCC'03).

23. Gregoire Mercier, Marie-Catherine Mouchot, and Guy Cazuguel, "Multitemporal SAR Image Compression" Proceedings of the 1998 International Conference on Image Processing (ICIP '98)

24. Zhaohui Zeng and Ian Cumming, "SAR Image Compression Based on the Discrete Wavelet Transform", Proceedings of ICSP '98.

25. M.Ancis, M,Murroni, D.D.Giusto , "Region-Based Remote-Sensing Image Compression in the Wavelet Domain" IEEE International Symposium on Geoscience and Remote Sensing , vol. 4 PP: 2054-2056, 1999.

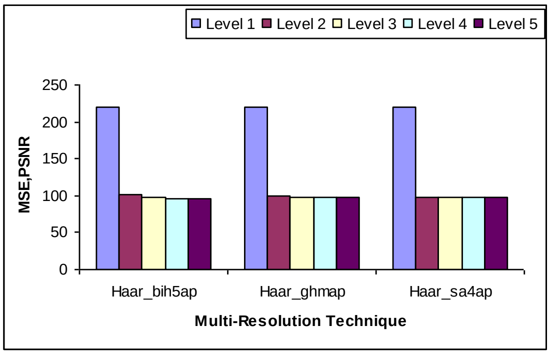


Figure1- Shows the MSE and PSNR at different level of decomposition

Wavelet Types			DL	Noisy Image		De-noised Image	
DF	**RF**	**PF**		**MSE**	**PSNR**	**MSE**	**PSNR**
haar	haar	bih5ap	1	1.7640E-05	220.2785	1.7640E-05	220.2785
			2	1.7650E-05	220.2728	2.5453E+00	101.4826
			3	1.7630E-05	220.2809	3.6418E+00	97.9004
			4	1.7631E-05	220.2836	4.0717E+00	96.784
			5	1.7640E-05	220.2766	4.2152E+00	96.4383
haar	haar	ghmap	1	1.7615E-05	220.2927	1.7615E-05	220.2927
			2	1.7627E-05	220.2861	3.0990E+00	99.5144
			3	1.7647E-05	220.2749	3.6478E+00	97.8839
			4	1.7630E-05	220.2843	3.8106E+00	97.4473
			5	1.7639E-05	220.2791	3.8566E+00	97.3275
haar	haar	sa4ap	1	1.7654E-05	220.2707	1.7654E-05	220.2707
			2	1.7652E-05	220.272	3.4177E+00	98.5355
			3	1.7645E-05	220.2758	3.8587E+00	97.3219
			4	1.7648E-05	220.2739	3.9703E+00	97.0368
			5	1.7631E-05	220.2838	4.0004E+00	96.9614

DF: Decomposition Filter, RF: Reconstruction Filters, PF: Pre-processing Filters,
DL: Decomposition Level,

Table-1: Shows the MSE and PSNR with varying level of decomposition