International Journal of Scientific Research Engineering & Technology (IJSRET) ISSN: 2278–0882
IEERET-2014 Conference Proceeding, 3-4 November, 2014

Separated Component-Based Restoration Of Speckled SAR Images

Satish Khande
PG(M.TECH. VLSI engineering) student, SGVU Jaipur (Rajasthan)
Email ID- satish.khande702@gmail.com

***Abstract*— The coherent nature of the synthetic aperture radar (SAR) imaginary process, detected images suffer from the multiplicative noise, commonly referred to as speckle. This noise often makes the interpretation of the data difficult for both automated algorithms and human observers. Several methods have been proposed for speckle reduction is to use a dictionary that can represent the features in the speckled images. However, such methods fail to capture important salient features such as texture. Namely, we would like to separate the image to its structure and texture components based on the algorithm suggested for SAR images in the following paper. In this paper we present a speckle reduction algorithm for restoration problem of SAR images so that the structure and texture components can be separately estimated with different dictionaries. To solve this problem, an iterative algorithm based on surrogate functional is proposed. This paper shows better results than state-of-the-art speckle reduction methods.**

***Index Terms*— Synthetic aperture radar (SAR), image restoration, multiplicative noise, speckle.**

II. INTRODUCTION

Image restoration concerns the removal or reduction of degradations which have occurred during the acquisition of the images. Such degradations may include noise. Imaging techniques using coherent illumination, such as synthetic aperture radar (SAR), ultrasound, holography, which generate coherent images are suffer from a multiplicative noise known as speckle [1]. Speckle noise is generated due to constructive and destructive interference of multiple echoes returned from each pixel.

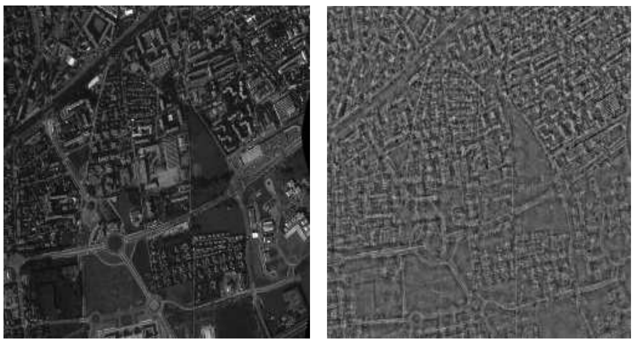
Many attempts were made to reduce the speckle noise. An appropriate method for speckle reduction is multi-look processing. In this method the synthetic aperture is divided into some pieces. Each of these apertures is processed separately to obtain a pixel with a special along-track dimension. However this often results in the reduction of the spatial resolution. Many different types of speckle reduction approaches are based on spatial local filter formation of the SAR image. Different filters have been developed that avoid the loss in spatial resolution [2] - [7]. These filters adapt themselves to the local texture information within a box surrounding a central pixel in order to calculate a new pixel value. Various wavelet-based transforms are used for the noisy image [8]-[13]. The wavelet transform is used in many applications in signal and image processing as in data

compression and signal de-noising, but also edge detection and texture characterization. Wavelet transform can represent a piecewise smooth image sparsely but it may also fail to represent an image with textures sparsely.

Total variation (TV) regularization [14], is an another approach for speckle noise removal. It is based on the principle that signals with excessive and possibly spurious details have high total variation. This noise removal technique has advantages over simple techniques such as linear smoothing or median filtering which reduce noise but at the same time smooth away edges to a greater or lesser degree. Many methods have been proposed for image restoration as use a combined dictionary.

A classical approach consists in considering that an image f can be decomposed into two components u+v. This is called cartoon and texture image component based restoration for SAR image [15]. The first component u is well-structured, and has a simple geometric description. The second component v contains both texture and noise. In proposed approach, u is estimated and is considered as the restored image and the texture components of v are not trying to be recovered. In this condition the texture components may result in the loss of important salient information in a SAR image. Fig.1 shows the example of structured and textured component based images.

Now, we present a separation based method that decompose image into a sum of piecewise smooth and textured elements. Our entire evaluation is based on finding spare representations of these elements dictionaries to compress them. Using help of sparse representation we are able to obtain important salient features and textured in the image.



(a) (b)

(c) (d)

Fig. 1. Image separation. (a) Original image. (b) Texture components. (c) Structural components. (d) Structural + texture components.

II. SEPARATION OF IMAGE

Many statistical models have been proposed for SAR images [16], [17]. In this paper, we use the logarithmic transform to convert the multiplicative noise into additive noise and take appropriate model for that noise.

Let y, f and x denote the ordered vector of size N^2 that is Y, F and X respectively. Now we assume that the SAR image with two different signals that is

$$X = x_p + x_t \qquad (1)$$

Where x_p denotes the piecewise smooth component and x_t denotes the textured component of x. According to the logarithmic transformation, the additive model that can be written as

$$Y = x + f$$
$$Y = x_p + x_t + f \qquad (2)$$

If we further assume that x_p is compressed in a dictionary and represented in the form of a matrix D_p and same for the x_t is compressed in a dictionary that represented in the form of a matrix D_t . for sparse representation of piecewise and texture components the dictionary $D_p \in R^{N2 \times Mp}$ and $D_t \in R^{N2 \times Mt}$ are selected where M_p, $M_t \geq N^2$ is given. There are coefficient vectors α_p and α_t so that $x_p = D_p\alpha_p$ and $x_t = D_t\alpha_t$. The texture dictionary D_t have oscillatory nature and D_p contains the structural feature such as edges.

The piecewise smooth component x_p and texture component x_t are estimating for SAR field x through α_p and α_t can recover the reflectivity of image.

$$\hat{\alpha}_p, \hat{\alpha}_t = \arg\min_{\alpha_p, \alpha_t} \lambda\|\alpha_p\|_1 + \lambda\|\alpha_t\|_1 + \gamma TV(\mathbf{D}_p\alpha_p) + \frac{1}{2}\|\mathbf{y} - \mathbf{D}_p\alpha_p - \mathbf{D}_t\alpha_t\|_2^2 \qquad (3)$$

Where TV is variations in image.

A. Iterative shrinkage algorithm

In this paper we present a fast convergent iterative shrinkage algorithm by using of separable surrogate functional (SSF). This method is solve the separation problem [18]-[20], for texture and piecewise smooth component posed in (3). For dictionary we assume D = [D_p, D_t]. Discard the TV component and equation (3) can then be rewritten as

$$f(\alpha) = \lambda\|\alpha\|_1 + \frac{1}{2}\|\mathbf{y} - \mathbf{D}\alpha\|_2^2 \qquad (4)$$

Where α holds both piecewise smooth and texture parts.
Let

$$d(\alpha, \alpha_0) = \frac{c}{2}\|\alpha - \alpha_0\|_2^2 - \frac{1}{2}\|\mathbf{D}\alpha - \mathbf{D}\alpha_0\|_2^2 \qquad (5)$$

Equations (4) and (5) added then surrogate function is

$$\tilde{f}(\alpha) = \lambda\|\alpha\|_1 + \frac{1}{2}\|\mathbf{y} - \mathbf{D}\alpha\|_2^2 + \frac{c}{2}\|\alpha - \alpha_0\|_2^2 - \frac{1}{2}\|\mathbf{D}\alpha - \mathbf{D}\alpha_0\|_2^2$$

We summarize the algorithm for restoring the two component of SAR image in Fig. 2.

Input: y, c.
Initialization: initialize k = 1 and set
$\mathbf{x}_p^0 = \mathbf{0}$, $\mathbf{x}_t^0 = \mathbf{0}$, $\mathbf{r}^0 = \mathbf{y} - \mathbf{x}_p^0 - \mathbf{x}_t^0$, and $\lambda^0 = \frac{1}{2}(\|\mathbf{D}_p^T\mathbf{y}\|_\infty + \|\mathbf{D}_t^T\mathbf{y}\|_\infty)$.
Repeat:
1.Update the estimate of x and x as

$$\tilde{\mathbf{x}}_p^k = \mathbf{D}_p\mathcal{S}_{\lambda^k}\left(\frac{1}{c}\mathbf{D}_p^T(\mathbf{r}^{k-1}) + \mathbf{D}_p^\dagger\tilde{\mathbf{x}}_p^{k-1}\right)$$
$$\mathbf{x}_p^k = \mathbf{H}\mathcal{S}_{\gamma^k}(\mathbf{H}^T\tilde{\mathbf{x}}_p^k)$$
$$\mathbf{x}_t^k = \mathbf{D}_t\mathcal{S}_{\lambda^k}\left(\frac{1}{c}\mathbf{D}_t^T(\mathbf{r}^{k-1}) + \mathbf{D}_t^\dagger\hat{\mathbf{x}}_t^{k-1}\right).$$

2.Update the residual as

$$\mathbf{r}^k = \mathbf{y} - \mathbf{x}_p^k - \mathbf{x}_t^k$$

3.Upadate the shrinkage parameter as

$$\lambda^k = \frac{1}{2}(\|\mathbf{D}_p^T\mathbf{r}^k\|_\infty + \|\mathbf{D}_t^T\mathbf{r}^k\|_\infty)$$

until: stopping criterion is satisfied.

Output: The two component is

$$\hat{\mathbf{x}}_p = \mathbf{x}_p^k \text{ and } \hat{\mathbf{x}}_t = \mathbf{x}_t^k .$$

Fig.2. SSF iterative shrinkage algorithm to solve (3).

The final estimation of x is obtain to denoised components of x.

$$\hat{\mathbf{x}} = \exp(\hat{\mathbf{x}}_p + \hat{\mathbf{x}}_t).$$

By this algorithm, it gives good results to compare with competitive methods. In this equations k indicates the value for kth iteration and H is the undecimated Haar wavelet transforms [21].

III. RESULTS AND COMPARISON

In this section, we compare the results from the proposed method with some new state-of- the- art methods such as Lee filter [2] and stein- block thresholding (SBT) method [22]. We also compare the our dictionary based approach with the wavelet- based thresholding (WT) and for MCA methods. For MCA method we use the curvelet transform to represent the piecewise smooth components and 2D-DCT to represent the texture component.

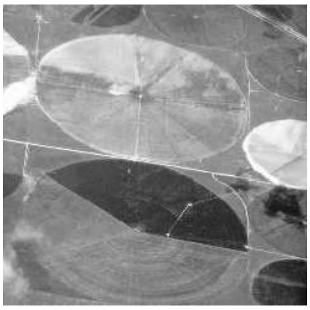
In fig. 2, the test example include three image sets and shows different experiment results. In these experimental results we use the relative error (RE) and the equivalent number of looks (ENL). By the use of these two we measure the performance of order tested is that,

$$RE = [\,\| \hat{x} - x \|_2] / [\,\| x \|_2]$$

$$ENL = mean^2 / \ variance$$

Here mean and variance are measured inside of homogeneous region.

In the Table 1 we can observed that the comparison of experiments values. In this computation our method is compared with the other methods for speckle reduction. Furthermore, the results in table 1 clearly indicate that an improvement is occurred when a combined dictionary approach is used for SAR images. As can be seen by comparing the results of our method with SBT, MCA and WT methods in table and shows the fig. 3 images.


(a)


(b)


(c)

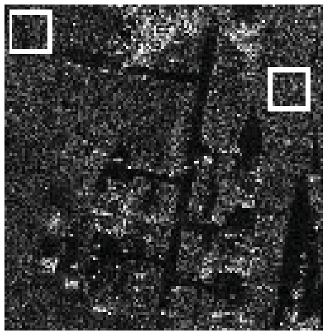
Fig. 3. Different experiments images: (a) Fields image. (b) Nimes image. (c) Cameraman image.

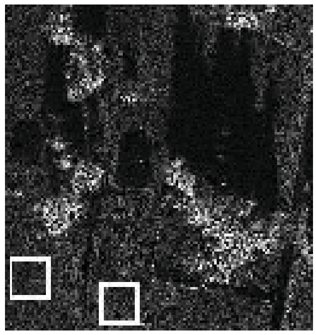
Table 1
Relative error for various experiments

Image	L	Noisy	SBT	WT	LEE	MCA	Proposed
Fields	1	1.000	0.114	0.159	0.135	0.110	0.099
Nimes	4	0.501	0.223	0.247	0.277	0.221	0.207
Nimes	1	1.001	0.312	0.346	0.298	0.320	0.290
Cameraman	10	0.315	0.111	0.105	0.171	0.101	0.090
Cameraman	4	0.498	0.144	0.135	0.178	0.140	0.118

Table 2
The estimated ENL values

Image	Region	Original	WT	SBT	LEE	MCA	Proposed
Fig.4(a)	R1	3.291	30.366	49.028	5.518	50.23	79.357
Fig.4(a)	R2	3.236	30.428	84.936	8.263	90.89	133.962
Fig.4(b)	R1	4.117	44.717	75.041	11.35	85.75	146.379
Fig.4(b)	R2	3.997	37.253	74.641	11.30	86.70	101.491


(a)


(b)


(c)


(d)

IV. CONCLUSION

In this paper, we discussed new component based method for the reduce speckle noise in SAR images. The proposed new method consists a specific dictionaries for structural and texture components. This dictionary represents the separation with an fast convergent iterative shrinkage scheme. It contains important salient features for SAR image. This paper also shows that comparison between proposed approach and various recent methods and obtained better results. The proposed method also valuable for many SAR images such as volcano scenes, coastline detection, road detection, railway detection and agricultural scenes.

V. REFERENCES

[1] J.W. Goodman, “Some fundamental properties of speckle,” J. Opt. Soc.Am., vol. 66, no. 11, pp. 1145–1150, Nov 1976.

[2] C. Oliver and S. Quegan, Understanding Synthetic Aperture Radar Images.Artech House, 1998.

[3] Y.-M. Huang, M. K. Ng, and Y.-W.Wen, “A new total variation method for multiplicative noise removal,” SIAM J. Img. Sci., vol. 2, no. 1, pp.20–40, January 2009.

[4] S. Durand, J. Fadili, and M. Nikolova, “Multiplicative noise removal using l1 fidelity on frame coefficients,” Journal of Mathematical Imaging and Vision, vol. 36, no. 3, pp. 201–226, 2010.

[5] J.-F. Aujol, G. Aubert, L. Blanc-Fraud, and A. Chambolle, “Image decomposition application to sar images,” in Scale Space Methods in Computer Vision, ser. Lecture Notes in Computer Science. Springer Berlin / Heidelberg, 2003, vol. 2695, pp. 297–312.

[6] F. Ulaby and M. C. Dobson, Handbook of Radar Scattering Statistics for Terrain. Norwood, MA: Artech House, 1989.

[7] H. Xie, L. Pierce, and F. Ulaby, “Statistical properties of logarithmically transformed speckle,” Geoscience and Remote Sensing, IEEE Transactions on, vol. 40, no. 3, pp. 721 –727, mar 2002.

[8] H. H. Arsenault and G. April, “Properties of speckle integrated with a finite aperture and logarithmically transformed,” J. Opt. Soc. Am., vol. 66, no. 11, pp. 1160–1163, Nov 1976.

[9] J.-L. Starck, M. Elad, and D. L. Donoho, “Image decomposition via the combination of sparse representations and a variational approach,” IEEE Transactions on Image Processing, vol. 14, no. 10, pp. 1570–1582, 2005.

[10] I. Daubechies, M. Defrise, and C. De Mol, “An iterative thresholding algorithm for linear inverse problems with a sparsity constraint,” Commun.Pure Appl. Math., vol. 57, pp. 1413–1541, 2004.

[11] M. Zibulevsky and M. Elad, “L1-l2 optimization in signal and image processing,” Signal Processing Magazine, IEEE, vol. 27, no. 3, pp. 76–88, may 2010.

[12] G. Steidl, J.Weickert, T. Brox, P.Mr´azek, andM.Welk, “On the equivalence of soft wavelet shrinkage, total variation diffusion, total variation regularization, and sides,” SIAM J.Numer. Anal., vol. 42, pp. 686–713, February 2004.
IEEE Transactions on Image Processing, vol. 16, no. 11, pp. 2675–2681, 2007.

[13] D. L. Donoho and J. M. Johnstone, “Ideal spatial adaptation by waveletshrinkage,” Biometrika, vol. 81, no. 3, pp. 425–455, 1994.

[14] J.-F. Aujol, G. Aubert, L. Blanc-Féraud, and A. Chambolle, “Image decomposition application to SAR images,” in Proc. 4th Int. Conf. Scale Space Methods Comput. Vis., 2003, pp. 297–312.

[15] J.-L. Starck, M. Elad, and D. L. Donoho, “Image decomposition via the combination of sparse representations and a variational approach,” IEEE Trans. Image Process., vol. 14, no. 10, pp. 1570–1582, Oct. 2005.

[16] F. Ulaby and M. C. Dobson, Handbook of Radar Scattering Statistics for Terrain. Norwood, MA, USA: Artech House, 1989.

[17] H. Xie, L. Pierce, and F. Ulaby, “Statistical properties of logarithmically transformed speckle,” IEEE Trans. Geosci. Remote Sens., vol. 40, no. 3, pp. 721–727, Mar. 2002.

[18] C. Tison, J.-M. Nicolas, F. Tupin, and H. Maitre, “A new statistical model for Markovian classification of urban areas in high-resolution SAR images,” IEEE Trans. Geosci. Remote Sens., vol. 42, no. 10, pp. 2046–2057, Oct. 2004.

[19] S. Sardy, A. G. Bruce, and P. Tseng, “Block coordinate relaxation methods for nonparametric wavelet denoising,” J. Comput. Graph. Stat., vol. 9, no. 2, pp. 361–379, 2000.

[20] M. Elad, Sparse and Redundant Representations: From Theory to Applications in Signal and Image Processing. New York, USA: Springer-Verlag, 2010.

[21] I. Daubechies, M. Defrise, and C. De Mol, “An iterative thresholding algorithm for linear inverse problems with a sparsity constraint,” Commun. Pure Appl. Math., vol. 57, no. 11, pp. 1413–1541, Nov. 2004.

[22] M. Zibulevsky and M. Elad, “L1-L2 optimization in signal and image processing,” IEEE Signal Process. Mag., vol. 27, no. 3, pp. 76–88, May 2010.