

# On the Implementation of Non Local Means Speckle Filter for Hybrid PolSAR data

Rakesh Sharma, *Student Member, IEEE* and R. K. Panigrahi, *Member, IEEE*

Department of Electronics and Communication Engineering, Indian Institute of Technology, Roorkee, India - 247667.

e-mail: r.sharma.in@ieee.org and rajibpanigrahi@ieee.org

**Abstract**—The non local means (NLM) filter for SAR and PolSAR data have best performance in terms of speckle reduction and preservation of sharp details. The speckle filtering of hybrid-pol data based on Stokes vector is absent in the literature. In this paper, the non local means speckle reduction algorithm is implemented for hybrid-pol SAR data in Stokes data format. The possibilities of using Stokes based NLM filter for hybrid-pol data is explored by evaluating the performance of filter for extent of speckle reduction, preservation of statistics, preservation of edges and classification results. The filter is applied to synthesized hybrid-pol data from full pol RADARSAT-2 data captured over San Francisco bay region. The algorithms are compared based on visual results, ENL, mean and standard deviation for estimated noise, edge preservation degree of ratio of average (EPD-ROA) and classification results with and without using speckle filters. It can be observed from the presented visual results that granular appearance is smoothed up for the homogeneous region (sea area) and edges & sharp details are preserved for heterogeneous regions. Further, numerically, Table II shows that polarimetry property of hybrid-pol data is not altered with despeckling. The Stokes based NLM filter provides a good trade-off in terms of performance measures considered in this paper.

**Index Terms**—Speckle filtering; NLM filter; hybrid-pol SAR; edge preservation; Stokes parameters.

## I. INTRODUCTION

Speckle is a stochastic and correlated noise (or interference pattern) in synthetic aperture radar (SAR) images. It arises due to coherent re-radiation from several scatterers in the radar resolution cell. Despeckling is the process of eliminating speckle noise from the SAR information signal. This is an essential and the foremost preprocessing step for SAR image processing in the field of remote sensing. Speckle noise is critical due to properties like its signal dependence and multiplicative nature. It degrades the image quality and information perception of high resolution images. The visual appearance of image is distorted and it makes information extraction and estimation difficult from the acquired images.

In recent past, the patch based non local filtering methods for speckle noise reduction of SAR and polarimetric SAR (PolSAR) have gained popularity because of their edge preserving capabilities along with efficient suppression of the speckle noise. The noise smoothing based on non local means (NLM filters) was proposed in [1], which have become a popular approach for despeckling of images in the recent times. The idea is to find the similarity or dissimilarity of reference SAR/PolSAR data point to all data points in the search window. The similar data points are weighted higher

as compared to dissimilar data points. The weighted average of all the data points in the search window is done to estimate the speckle free data. The search window sizes are of the order typically  $5 \times 5$ ,  $7 \times 7$ ,  $9 \times 9$ , and so on. A non local based pretest filtering approach for PolSAR data is proposed in [2]. It is based on the principle that covariance matrix of the PolSAR data is Wishart distributed and hence the test statistic is defined to check for the homogeneity of two pixels. For each pixel of the PolSAR image, set of homogeneous pixels are identified and are used for speckle filtering of the reference pixel. The pretest approach works efficiently in eliminating speckle noise and retaining point targets and sharp edges, but is complex and time consuming. The comprehensive literature survey of SAR speckle filtering and non local patch based filtering of SAR images is given in [3], [4]. It focused on discussion of various patch based despeckling methods by measurement of patch similarity and estimation of parameters from the set of similar patches. The need of preservation of the polarimetric property is the prime requirement in land cover classification applications [5]. And hence many techniques which are defined based on statistical distances or SAR/PolSAR speckle statistics are modified in accordance with scattering information of the data [6]. The hybrid-pol configuration pose advantages as compared to full-pol SAR configurations. The full-pol SAR suffers from limitations of double pulse repetition frequency, double average transmit power, half swath coverage and higher data volume. The advancements in processing of hybrid-pol data are carried out targeting classification performance close to that of full-pol configurations and overcoming its limitations. The processing of hybrid-pol data is in the initial phase and different decomposition & classification methods are being developed [7–9]. In order to despeckle the hybrid PolSAR data, the hybrid data in covariance matrix is applied to the speckle filtering algorithms. However, the speckle filtering algorithms where the input is Stokes vector is absent in the literature. In this paper, the Stokes vector and Wishart distance based NLM filter for hybrid-pol data is analyzed. This paper is an attempt to extend the speckle filters defined for full-PolSAR data to hybrid-pol SAR data. The effectiveness in reducing speckle can be clearly seen on the synthesized hybrid PolSAR datasets from RADARSAT-2 SAR sensor.

## II. HYBRID POLSAR CONFIGURATION

In the hybrid PolSAR configuration, circularly polarized wave is transmitted and is received with two orthogonal linear

polarizations H and V. It is also known as circular polarization transmit and linear receive (CTLR). The hybrid-pol configuration is able to reconstruct the partial full-pol information from dual-pol information [7], [10]. Each pixel of the acquired hybrid-pol data is characterized by a backscattering vector  $\mathbf{E}_{\text{hyb}}$ ,

$$\mathbf{E}_{\text{hyb}} = [E_{RH} \ E_{RV}] \quad (1)$$

where,  $E_{RH}$  and  $E_{RV}$  are the backscattered signal with right hand circular transmission and reception with horizontally and vertically polarized antennas, respectively. The backscattered vector is further used to generate covariance matrix  $\mathbf{C}_{\text{hyb}}$ .

$$\mathbf{C}_{\text{hyb}} = \langle \mathbf{E}_{\text{hyb}} \cdot \mathbf{E}_{\text{hyb}}^H \rangle \quad (2)$$

The scattering information in hybrid PolSAR data is best characterized by the corresponding Stokes vector. The Stokes vector can be derived from received backscattered signal.

$$\mathbf{g} = \begin{bmatrix} g_0 \\ g_1 \\ g_2 \\ g_3 \end{bmatrix} = \begin{bmatrix} \langle |E_{RH}|^2 + |E_{RV}|^2 \rangle \\ \langle |E_{RH}|^2 - |E_{RV}|^2 \rangle \\ 2 \langle \Re(E_{RH} E_{RV}^*) \rangle \\ 2 \langle \Im(E_{RH} E_{RV}^*) \rangle \end{bmatrix}. \quad (3)$$

The  $g_0$  is the total power in the backscattered signal. The  $g_1$ ,  $g_2$  and  $g_3$  are the difference of backscattered intensities in the orthogonal channels, in orthogonal channels rotated at  $\pi/4$  and in right and left hand circularly polarized components, respectively. The conventional speckle filtering algorithms are applied on covariance matrix defined in (2). In this paper, the speckle filtering is applied on Stokes vector. This is followed by the decomposition methods of hybrid-pol data for land cover classification. The  $m - \chi$  decomposition method [8] is chosen here for estimating the three basic power contributions. The power contributions  $P_s$ ,  $P_v$  and  $P_d$  due to surface, volume and double bounce scattering, respectively based on  $m - \chi$  decomposition method are

$$\begin{bmatrix} P_s \\ P_v \\ P_d \end{bmatrix}_{m-\chi} = \begin{bmatrix} \sqrt{g_0 m (1 \pm \sin 2\chi)} \\ \sqrt{g_0 (1 - m)} \\ \sqrt{g_0 m (1 \mp \sin 2\chi)} \end{bmatrix} \quad (4)$$

where upper '+/-' signs in  $P_s$  &  $P_d$  are for left hand circular polarization transmission and lower '-/+' signs in  $P_s$  &  $P_d$  are for right hand circular polarization transmission. The parameters  $m$  and  $\chi$  for  $m - \chi$  decomposition are calculated as follows.

$$m = \frac{\sqrt{(g_1^2 + g_2^2 + g_3^2)}}{g_0} \quad (5)$$

$$\sin(2\chi) = -\frac{g_3}{m g_0}$$

The NLM filtering based on Stokes vector is discussed in the next section.

### III. NON LOCAL MEANS DESPECKLING

In this section, the steps for NLM filtering of hybrid PolSAR data are discussed. The Stokes vector  $\mathbf{g}$  of the reference pixel  $x$  is compared with the surrounding Stokes vectors  $\mathbf{g}'$  in the search window  $S \times S$  centered around the reference pixel  $x$ . The pixel similarity and dissimilarity of the Stokes vectors is defined by  $L_2$  norm and is computed by

$$\delta(\mathbf{g}, \mathbf{g}') = \|\mathbf{g} - \mathbf{g}'\|^2 \quad (6)$$

The similarity measure is used to calculate the weight such that similar patches are assigned larger weights as compared to dissimilar ones. The weights can be computed by the popular exponential kernel and is given by

$$w(\mathbf{g}, \mathbf{g}') = \exp(-\delta(\mathbf{g}, \mathbf{g}')/h) \quad (7)$$

where  $h$  is the noise smoothing parameter.

The NLM filtered estimate  $\mathbf{g}^{NL}(x)$  of the reference pixel at  $x$  is given by (8).

$$\mathbf{g}^{NL}(x) = \frac{\sum_{j \in S} w(\mathbf{g}(x), \mathbf{g}(x_j)) \mathbf{g}(x_j)}{\sum_{j \in S} w(\mathbf{g}(x), \mathbf{g}(x_j))} \quad (8)$$

The similarity measure between Stokes vector can also be calculated by the Wishart distance measure. The distance measure can be applied to covariance matrix which is Wishart distributed. The similarity between two Wishart distributed covariance matrices  $\mathbf{X}$  and  $\mathbf{Y}$  can be defined as

$$\delta(\mathbf{X}, \mathbf{Y}) = \log Q = n(2q \log 2 + \log |\mathbf{X}| + \log |\mathbf{Y}| - 2 \log |\mathbf{X} + \mathbf{Y}|) \quad (9)$$

where  $n$  is number of looks and  $q$  is dimension of the covariance matrix [2]. However, it is not required to convert the Stokes data to covariance matrix as  $\text{absdet}(\mathbf{X})$  can be calculated in terms of  $\mathbf{g}$  as in (10).

$$|\mathbf{X}| = \frac{g_0^2 - g_1^2}{4} - \frac{g_2^2 + g_3^2}{4} \quad (10)$$

The  $\delta(\mathbf{X}, \mathbf{Y})$  can be easily converted to  $\delta(\mathbf{g}, \mathbf{g}')$  and hence the similarity measure can be converted to Stokes vector format. The algorithm for NLM filtering is given below.

**Input:** Hybrid PolSAR data

**Output:** Filtered PolSAR data

*Initialisation:* Smoothing constant  $h$  and search window size  $S$

*LOOP Process*

- 1: **for**  $i_1 = 1$  to number of pixels **do**
- 2:   **for**  $i_2 \in S$  in search window **do**
- 3:     Find out  $\delta(\mathbf{g}(i_1), \mathbf{g}(i_2))$
- 4:     Find out  $w(\mathbf{g}(i_1), \mathbf{g}(i_2))$
- 5:   **end for**
- Calculate  $\mathbf{g}^{NL}(i_1)$
- 6: **end for**
- 7: **return** Filtered Image  $\mathbf{g}^{NL}$

### IV. RESULTS AND DISCUSSION

The effectiveness of NLM filter for speckle reduction is demonstrated by applying it to the synthesized hybrid PolSAR data sets. The single look full-pol data is from RADARSAT-2 C-band SAR sensor captured over San Fransisco bay area. The data is  $14416 \times 2823$  pixels and for demonstration purposes a portion of  $1000 \times 600$  pixel is selected. The data is synthesized to be hybrid-pol as it is standard valid data set and full-pol classification results are available for this data set.

The NLM filter is applied to synthesized hybrid-pol data and visual results are presented in Fig. 1. The visual inspection of images confirm the speckle reduction and noise smoothing. The effectiveness of speckle reduction is evaluated by

Table I  
EVALUATION OF SPECKLE REDUCTION EFFECTIVENESS. THE EQUIVALENT NUMBER OF LOOKS (ENL), MEAN  $\mu_r$  AND STANDARD DEVIATION  $\sigma_r$  OF POINT TO POINT RATIO OF NOISY BY FILTERED IMAGE AND EPD-ROA COMPARISON.

Filter	ENL	$\mu_r$	$\sigma_r$	EPD-ROA
Noisy	0.96	-	-	1
Box Car	19.59	0.997	0.95	0.45
Lee Sigma	7.67	0.93	0.67	0.52
Stokes based NLM	9.89	0.99	0.83	0.61
NLM Wishart	9.51	0.92	0.77	0.49

Table II  
CLASSIFICATION RESULTS FOR  $1000 \times 600$  PIXEL PORTION OF SYNTHESIZED HYBRID POL DATA FROM SINGLE LOOK FULL POL RADARSAT-2 DATA.

Method	$P_s$ (%)	$P_d$ (%)	$P_v$ (%)
Yamaguchi 4 component	60.17	21.40	18.42
Noisy Image	65.42	34.56	0
Box Car filter	38.68	7.98	53.34
Lee Sigma	40.70	7.09	52.20
Stokes based NLM	40.82	6.80	51.31
NLM Wishart	47.85	16.04	35.25

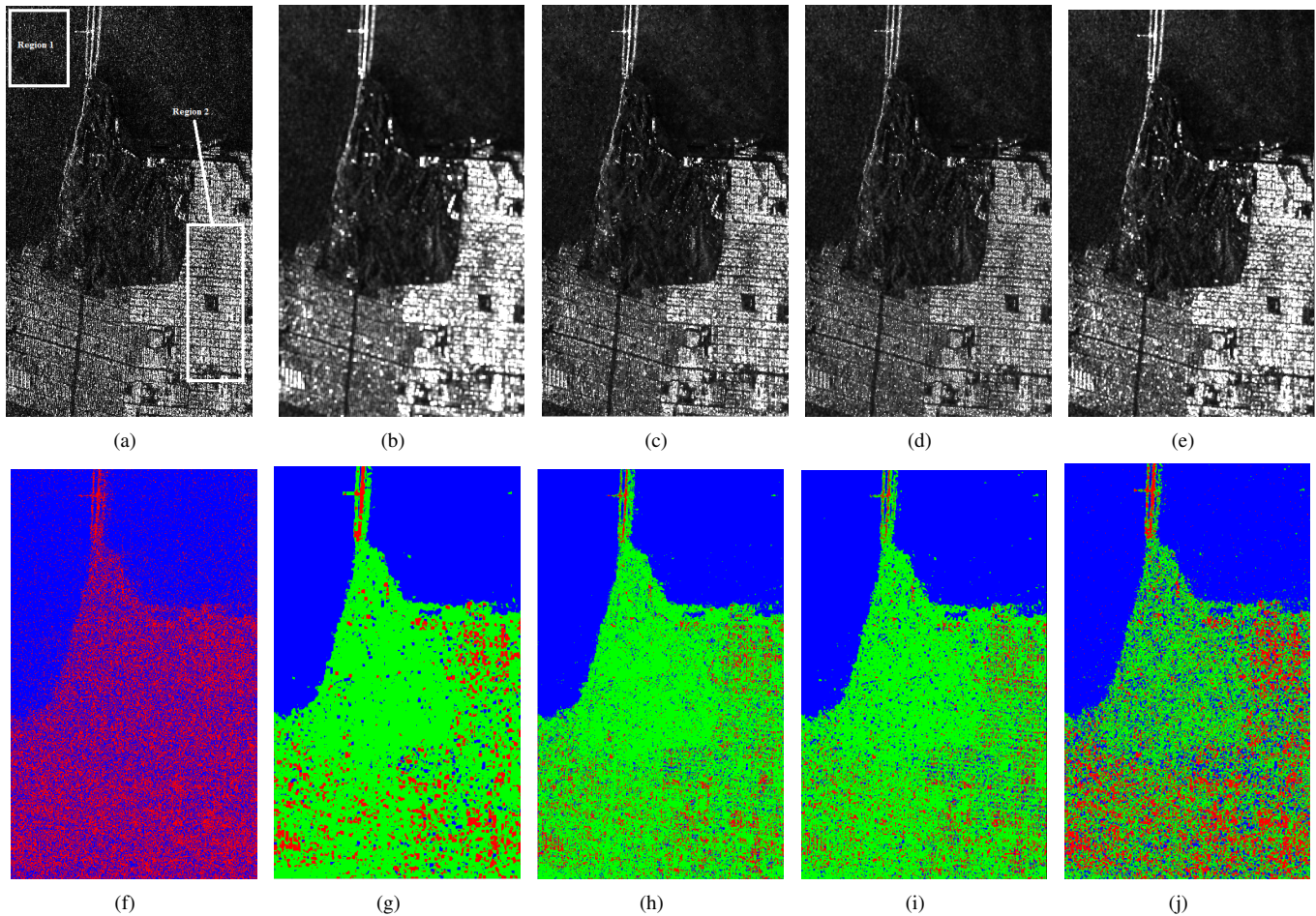


Figure 1. Comparison of span images and RGB classified images for a portion of  $1000 \times 600$  pixels of synthesized hybrid pol data. (a) The noisy intensity image (b) Box Car Filter (c) Lee Sigma Filter, window size 7 and filter size 3 (d) Stokes based NLM filter window size 5 (e) Wishart NLM filter window size 5 (f) noisy RGB classified image (g) Box Car filter (h) Lee Sigma filter (i) Stokes based NLM filter (j) Wishart NLM filter.

Equivalent number of looks (ENL) [3], a standard parameter to measure noise smoothness over homogeneous areas. It can be estimated by

$$ENL = \left( \frac{E(g_{0,F})}{\text{std}(g_{0,F})} \right)^2$$

where  $g_{0,F}$  is the filtered  $g_0$  image. Higher value of ENL implies higher speckle reduction. The comparison of mean and standard deviation of the ratio image noisy by filtered  $g_0$  image is evaluated. Ideally the mean and standard deviation of the ratio image should be unity. The edge preservation capability is estimated by a parameter edge preservation degree of ratio of average (EPD-ROA) [11]. It can be calculated for the heterogeneous region by

$$\text{EPD-ROA} = \frac{\sum_{j=1}^l g_{0,F}(j)/g_{0,F}(j+HorV)}{\sum_{j=1}^l g_0/g_0(j+HorV)} \quad (12)$$

where  $g_{0,F}(j+HorV)$  is the filtered  $g_0$  value at horizontally or vertically adjacent value of  $j$  and  $l$  is the number of data points in the search window. The value should be ideally close to unity. The quantitative result comparison is presented in Table I. The Stokes based NLM and Wishart NLM is compared with state of art Box Car and Lee Sigma filter [12]. Table I shows the improvement in ENL of filtered images over noisy image. The homogeneous (Region 1) and heterogeneous (Region 2) are considered as shown in Fig. 1(a). The ENL is highest for Box Car filter but at the expense of blurring of sharp details. The EPD-ROA is 45% for Box Car filter. The Stokes based filter provides better trade off between the speckle reduction and details preservation. The EPD-ROA is highest at 61% when compared with other speckle filtering algorithms. Also, the mean and standard deviation of ratio image are more closer to ideal values and only second best to Box Car filter. The latter have poor trade off between speckle reduction and detail preservation. The Lee sigma filter have results inferior to that of Stokes based NLM filter. The Stokes based NLM and NLM Wishart are compared for nearly same ENL value and latter leads to poor mean, standard deviation and details preservation. This is due to the fact that for single look data the Wishart distance measure estimate is biased [12].

The classification results are presented in Table II. This also confirms the fact that the NLM filter implemented does not degrades the scattering property of hybrid PolSAR data. The Stokes based NLM filter preserves the scattering information as done in case of Box Car and Lee Sigma filter. However for NLM Wishart, the classification results are some what inferior. The  $P_s$ ,  $P_d$  and  $P_v$  power contribution percentage for  $1000 \times 600$  portion is given for all the filtered images in Table II. The reference can be taken as full pol Yamaguchi Four component decomposition image.

The visual result comparison is presented in Fig. 1. The (b) and (e) are blurred as compared to (c) and (d). The span image for Stokes based NLM filter is best in terms of speckle reduction and details preservation. The processing time for Stokes based and Wishart NLM algorithm is approx. 49 and 82 seconds, respectively for the image size of  $1000 \times 600$  pixels on an Intel machine having CPU 2.5 GHz with memory 16 GB.

## V. CONCLUSION

The speckle filters for hybrid-pol data explicitly in Stokes format is not available in the literature. The NLM speckle filters based on euclidean distance and Wishart distance of

Stokes vector are implemented for hybrid-pol data. The effect on classification results is studied and found that Stokes based NLM filter preserves the scattering information better than Wishart based NLM. The simulation results clearly shows the effectiveness of Stokes based NLM filter in reducing speckle of hybrid-pol data and preservation of fine details. The classification results are unchanged which means the polarization information is not altered. The ENL of Stokes based NLM and Wishart based NLM is second best to Box Car filter. However, the EPD-ROA is best for Stokes based NLM for all the compared algorithms. In terms of preservation of statistics, the Stokes based NLM performs only second best to Box Car which suffers from major limitation of blurring the fine details. Overall the Stokes based NLM filter is a good alternative for speckle reduction of hybrid PolSAR data. The Wishart based NLM filter is good in terms of speckle filtering but found unsuitable in terms of preservation of fine details, data statistics and scattering information. The major reason may be its biased Wishart distance estimation single look data.

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