

SPATIALLY ADAPTIVE DESPECKLING FOR MULTI-LOOK POLARIMETRIC SYNTHETIC APERTURE RADAR IMAGERY

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ABSTRACT: A spatially adaptive speckle filtering approach for multi-look polarimetric synthetic aperture radar imagery is presented. The central idea of the proposed filter is that the filtering operations are performed spatially variant for image features, i.e. edges, lines and point-like textural features, in order to preserve them. For homogeneous areas, the filtering is based on scattering properties. To achieve this, edge detection, line detection, texture analysis and classification based on scattering properties are carried out, followed by a final despeckling. The capabilities of the proposed filter were examined in terms of speckle removal, image feature retention as well as radiometric preservation by using nine-look NASA/JPL POLSAR data. Moreover, the filtering impacts on the Cloude-Pottier target decomposition parameters, namely alpha-angle, entropy and anisotropy, were investigated in this paper.

1. INTRODUCTION

Polarimetric synthetic aperture radar (POLSAR) data are inherently corrupted by speckle noise. This presence of speckle noise may degrade the performance of post-processing applications, such as image segmentation and classification. To date, numerous speckle filtering methods have been proposed for POLSAR data. Novak and Barl (1990) pioneered the area of speckle reduction in POLSAR data by introducing a polarimetric whitening filter for single-look POLSAR data. In order to filter the complete covariance matrix in multi-look POLSAR data, Lee et al. (1999) derived a speckle filter based on linear minimum mean-square estimation. Schou and Skriver (2001) extended the annealing filter, which was originally proposed for single-frequency single-polarisation SAR data, by making use of a complex Wishart distribution and maximum likelihood estimation. In another work, a classified pixel-based windowing technique was presented by Yoon and Kim (2003) for POLSAR speckle filtering, where the classification involves the use of the underlying scattering information. In a further paper with the objective to preserve the scattering properties, Lee et al. (2006) proposed a speckle filter that includes only those pixels of the same scattering characteristics in the computation of the average. The employed classification method is a combination of the Freeman-Durden three-component scattering model and the complex Wishart classifier.

In this paper a spatially adaptive filtering approach is introduced for multi-look POLSAR data, which aims at preserving point-like textural features as well as structural features, i.e. edges and lines, during speckle filtering process. This paper is organised as follows: Section 2 explains the proposed spatially adaptive filtering approach. The experiments and results are discussed in Section 3. Finally, Section 4 concludes the paper.

2. PROPOSED SPATIALLY ADAPTIVE FILTERING APPROACH

Similar to the speckle filter presented in Lee and Breitschneider (2006b), the proposed filtering approach consists of five steps, namely edge detection, line detection, texture analysis, classification based on scattering mechanisms, and despeckling. The main difference between the two speckle filters is that no filtering is performed by the previously proposed filter to remove the speckle noise in image features, i.e. edges, lines and point-like textural features. Furthermore, the trace ratio edge detector is replaced, in this proposed filtering approach, by a so-called Roy’s largest eigenvalue-based edge detector. In the following each processing step is explained in more detail.

2.1 Edge Detection

To detect edges in multi-look POLSAR imagery, Roy’s largest eigenvalue-based edge detector, which was proposed by Lee and Breitschneider (2006a), is employed. The edge detector is formulated based on an equality test of two Hermitian covariance matrices following the union-intersection principle.

In L-look POLSAR data each pixel can be represented by a $p \times p$ Hermitian covariance matrix $\mathbf{C}$. Multiplying the covariance matrix with the number of looks, the matrix $\mathbf{Z} = L\mathbf{C}$ can be assumed to follow a central complex Wishart distribution $CW(p, L, \Sigma)$ with a population covariance matrix $\Sigma$. For the purpose of edge detection, the Roy’s largest eigenvalue test statistic is expressed as

$$\lambda_{Roy} = \max\{ch_1(\mathbf{Z}_1, \mathbf{Z}_2), ch_1(\mathbf{Z}_2, \mathbf{Z}_1)\},$$

where $ch_1(\mathbf{Z}_1, \mathbf{Z}_2)$ is the largest eigenvalue of $\mathbf{Z}_1, \mathbf{Z}_2$ and max denotes the maximum operator. Figure 1 shows four basic edge templates of 3×3 pixels with different orientations. In each edge template, there are two equally
sized contiguous test regions, namely $r_1$ and $r_2$, containing the same number of pixels, i.e. $m = 3$ for a $3 \times 3$ edge template. Let the complex Wishart matrices $Z_1, Z_2, \ldots, Z_m$ in the test region $r_1$ be mutually independent, then the summation of these matrices is also complex Wishart distributed as $CW(p, L_1 + L_2 + \ldots + L_m, \Sigma_1)$ (Andersen et al., 1995, p. 43) and the matrix

$$ Z_{r_1} = \left( \sum_{i=1}^{m} L_i C_i \right) / \sum_{i=1}^{m} L_i $$

(2)

is the maximum likelihood estimator for $\Sigma_1$. The matrix $C_i$ in the above equation refers to the Hermitian covariance matrix of a pixel $i$ within the test region $r_1$. Using (2) equivalently for the test region $r_2$, the Roy’s largest eigenvalue test statistic in (1) can be solved.

From (1), it is clearly noticed that the Roy’s largest eigenvalue-based edge detector is a symmetrical detector, which is independent of the scanning direction (Touzi et al., 1988, p. 766). Because of the used maximum operator in (1), the computed value of $\lambda_{Roy}$ belongs to the interval of $[1, \infty)$. If $Z_{r_1}$ and $Z_{r_2}$ are equal, then the matrix $Z_{r_1}Z_{r_2}^{-1}$ is an identity matrix with unit eigenvalues. Thus, the eigenvalue $\lambda_{Roy}$ is unity for a perfectly homogeneous area. On the contrary, it differs from unity if a discontinuity exists within the tested edge template.

Figure 1: $3 \times 3$ edge templates with orientations (a) 0°, (b) 45°, (c) 90° and (d) 135°. The two test regions $r_1$ and $r_2$ are coloured in yellow and magenta, respectively.

For detecting edges in multi-look POLSAR imagery, the involved processing steps are outlined below:
1. Place all edge templates over a pixel $i$.
2. Estimate $Z_{r_1}$ and $Z_{r_2}$ for each edge template based on (2).
3. Compute the Roy’s largest eigenvalue for each edge template using (1).
4. Record the maximum of the computed Roy’s largest eigenvalues in Step 3.
5. Move the edge templates to the next pixel and repeat Steps 1–4. Terminate the execution if there are no more pixels to be processed.

Afterward, two thresholds, namely $e_{lower}$ and $e_{upper}$, are estimated from the obtained maximum Roy’s largest eigenvalue output and employed in the subsequent computation of the edge strength of each pixel. The threshold selection procedures are explained as follows:
1. Select a speckle-corrupted homogeneous area from the multi-look POLSAR image.
2. Compute the average of the maximum Roy’s largest eigenvalues of the pixels within the selected homogeneous area. Use it as the lower threshold, i.e. $e_{lower}$.
3. Construct the cumulative relative frequency plot for the maximum Roy’s largest eigenvalues of the pixels within the selected homogeneous area.
4. Determine the class interval which the cumulative relative frequency value of 0.990 falls into. Other cumulative relative frequency value can be specified by the user.
5. Compute the class midpoint and use it as the upper threshold, i.e. $e_{upper}$.

Using the two thresholds, the edge strength $s_{edge}$ for each pixel is computed as

$$ s_{edge} = \begin{cases} 0 & \lambda_{Roy} \leq e_{lower} \\ \frac{\lambda_{Roy} - e_{lower}}{e_{upper} - e_{lower}} & e_{lower} < \lambda_{Roy} < e_{upper} \\ 1 & \lambda_{Roy} \geq e_{upper} \end{cases} $$

(3)

For a homogeneous area, the value of $s_{edge}$ is zero, while it is equal to unity for a confirmed edge. The edge strength is used in Subsection 2.5 for defining the filtering weight. In fact, (3) shows the fuzzy mapping of the edgeness, which is identical to the fuzzy edge detection presented by Jeansoulin et al. (1981, p. 337).

2.2 Line Detection

The Roy’s largest eigenvalue-based edge detector can be applied for line detection by using line templates in (1). Figure 2 shows four $3 \times 3$ line templates with different orientations. Likewise, two line thresholds $l_{lower}$ and $l_{upper}$ are set in the same way as discussed in the previous subsection. The line strength $s_{line}$ is subsequently computed for each pixel as

$$ s_{line} = \begin{cases} 0 & \lambda_{Roy} \leq l_{lower} \\ \frac{\lambda_{Roy} - l_{lower}}{l_{upper} - l_{lower}} & l_{lower} < \lambda_{Roy} < l_{upper} \\ 1 & \lambda_{Roy} \geq l_{upper} \end{cases} $$

(4)

For a homogeneous area, the value of $s_{line}$ is zero, while it equals unity for a confirmed line.
2.3 Texture Analysis

For characterising the intrinsic texture or spatial heterogeneity in POLSAR data, a relative dispersion measure is proposed and defined by the ratio of the root mean square deviation to the average overall variability, i.e.

\[ D = \sqrt{d^2(C_k, C_{\text{average}})} / \text{tr}(C_{\text{average}}) \]  

with

\[ d^2(C_k, C_{\text{average}}) = \sum_i \sum_j (a_{ij} - b_{ij})^2. \]

The deviation \( d(C_k, C_{\text{average}}) \) is the Euclidean distance between two matrices \( C_k \) and \( C_{\text{average}} \), which is given in (Hartfiel, 2001, p. 117). The matrices \( C_k \) and \( C_{\text{average}} \) are the covariance matrix of a pixel \( p_k \) and the average covariance matrix within a local window, respectively. Both \( a_{ij} \) and \( b_{ij} \) refer separately to the elements of the matrices \( C_k \) and \( C_{\text{average}} \). It is important to note that the Euclidean distance has no immunity against the multiplicative noise in POLSAR intensities. However, as it can be seen in (5), a ratio operation is employed in the dispersion measurement, which actually helps to cope with the multiplicative noise disturbance.

For larger window sizes, it is advisable to use a spatially weighted dispersion measure instead. The following spatially weighted versions of \( C_{\text{average}} \) as well as \( \{d^2(C_k, C_{\text{average}})\} \) are computed and substituted into (5):

\[ C_{\text{average}} = \frac{\sum_{k=1}^{N} w_k C_k}{\sum_{k=1}^{N} w_k} \]

and

\[ \{d^2(C_k, C_{\text{average}})\} = \frac{\sum_{k=1}^{N} w_k d^2(C_k, C_{\text{average}})}{\sum_{k=1}^{N} w_k}, \]

where the weight has the following form

\[ w_k = \exp\left(-\sqrt{(x_k - x_0)^2 + (y_k - y_0)^2}\right). \]

The variable \( N \) denotes the total number of pixels within the test window. The variables \( x_k \) and \( y_k \) are the \( x \)- and \( y \)-axis coordinates for a pixel \( p_k \) within the window, while \( x_0 \) and \( y_0 \) are the coordinates of the central pixel. The notation exp refers to the exponential function.

With the generated relative dispersion output, the strength of the spatial heterogeneity \( s_{\text{texture}} \) is computed as

\[ s_{\text{texture}} = \begin{cases} 
0 & \text{if } D < D_{\text{lower}} \\
(D - D_{\text{lower}}) / (D_{\text{upper}} - D_{\text{lower}}) & D_{\text{lower}} < D < D_{\text{upper}} \\
1 & \text{if } D \geq D_{\text{upper}} 
\end{cases}, \]

where the thresholds \( D_{\text{lower}} \) and \( D_{\text{upper}} \) are determined by compiling the corresponding statistics as discussed in Subsection 2.1 from a selected speckle-corrupted homogeneous area.

2.4 Classification Based on Scattering Mechanisms

The three-component scattering model, which was proposed by Freeman and Durden (1998), is employed to retrieve the scattering properties in POLSAR data. The contributions of surface scattering \( P_s \), double-bounce scattering \( P_d \) as well as volume scattering \( P_v \) in each pixel are computed. Each pixel is then classified into a scattering class \( S_c \) by comparing the three scattering contributions:

\[ S_c = \begin{cases} 
c = 1 & \text{if } P_d > P_s > P_v \\
c = 2 & \text{if } P_d > P_v > P_s \\
c = 3 & \text{if } P_v > P_s > P_d \\
c = 4 & \text{if } P_s > P_d > P_v \\
c = 5 & \text{if } P_s > P_v > P_d \\
c = 6 & \text{if } P_d > P_s > P_v \\
c = 7 & \text{otherwise}
\end{cases}. \]
Note that the above classification is a modified version of the scheme proposed by Borghys (2001, p. 159). The obtained classification result is used in the following subsection for estimating the filtered covariance matrix.

### 2.5 Despeckling

With the computed feature strengths $s_{\text{edge}}, s_{\text{line}}$ as well as $s_{\text{texture}}$ the estimation of the filtered covariance matrix for a given pixel is solved by

$$
\hat{C} = wC_{\text{spatial}} + (1 - w)C_{\text{scatter}},
$$

where

$$
w = \max\{s_{\text{edge}}, s_{\text{line}}, s_{\text{texture}}\}.
$$

The matrices $C_{\text{spatial}}$ and $C_{\text{scatter}}$ are the filtered covariance matrices based separately on the spatial and scattering properties. The operator max denotes the maximum operation. From (12), it is obvious that $\hat{C} = C_{\text{scatter}}$ if the weight $w$ is zero. This means that the currently processed pixel is part of a homogeneous area and, thus, the filtering is performed based on the scattering properties. If $w$ equals unity, the currently processed pixel is found to be an edge pixel, a line pixel or part of a highly heterogeneous area. Hence, the filtered covariance matrix is computed based on the spatial properties.

To estimate $C_{\text{scatter}}$, the scattering class contributing the majority within the test window is identified first. If the total number of pixels which belong to the dominant scattering class is greater than or equal to a heuristically chosen 70%, then the average covariance matrix is computed as $C_{\text{scatter}}$ by using all pixels within the window that belong to this dominant class. For the case where the total number of pixels of the dominant class is less than 70%, the filtered covariance matrix is computed by taking both the spatial distances and the proportions of the different scattering classes into account:

$$
C_{\text{scatter}} = \left( \sum_{k=1}^{N} \text{dist}(p_k) \sum(S_k) C_{k,c} \right) / \left( \sum_{k=1}^{N} \text{dist}(p_k) \sum(S_k) \right),
$$

where $C_{k,c}$ is the covariance matrix of a pixel $p_k$ belonging to scattering class $S_k$. The variable $N$ denotes the total number of pixels within the test window, while $\sum(S_k)$ represents the total number of pixels within the window that belong to scattering class $S_k$. The value of $\text{dist}(p_k)$ is equal to $1/(1 + d_k)$, where

$$
d_k = \sqrt{(x_0 - x_k)^2 + (y_0 - y_k)^2}.
$$

For the matrix $C_{\text{spatial}}$, it is defined as

$$
C_{\text{spatial}} = \frac{\sum_{k=1}^{N} w_k C_k}{\sum_{k=1}^{N} w_k},
$$

with the weight of the form

$$
w_k = \exp(-d_k h_k).
$$

The weight $w_k$ consists of two measures, namely spatial distance $d_k$ and spatial heterogeneity $h_k$. The spatial distance measure refers to the Euclidean distance defined similarly in (15), while the spatial heterogeneity measure is given by

$$
h_k = d(C_k, C) / \text{tr}(C).
$$

The matrix $C$ denotes the covariance matrix of the currently processed pixel and $d(C_k, C)$ is again the Euclidean distance between two matrices. The spatial heterogeneity is computed with respect to the currently processed pixel, i.e. the central pixel within the test window. From (17), it is obvious that the weighting is decreased with an increase in both the spatial distance and spatial heterogeneity.

### 3. RESULTS AND DISCUSSION

In this study nine-look NASA/JPL POLSAR C-band data of Kuala Muda were used for demonstration. The detailed descriptions of the POLSAR test data and the scattering classification results are provided in Lee and Bretschneider (2005). Four window sizes, namely $3 \times 3$, $5 \times 5$, $7 \times 7$ and $9 \times 9$ pixels, were tested for speckle suppression. Figure 3 presents selected filtering results.

In order to evaluate the effectiveness of speckle removal quantitatively, the signal-to-noise ratio (SNR) over a homogeneous rubber plantation area was computed from the total power output. Note here that SNR is defined as the ratio of mean value to standard deviation. Based on the obtained results in Table 1, the SNR improved significantly for all test windows where the improvement was directly proportional to the increased window sizes. Furthermore, Figure 4 shows the total power surface plots extracted from the selected rubber plantation area. Through visual inspection of Figure 4, the speckles were found to be effectively removed, where a relatively smooth appearance can be distinctly observed, especially for the larger test windows.
For the assessment of radiometric preservation, the co-polarisation signatures of an oil palm plantation area are plotted in Figure 5. Additionally, the elements of the average covariance matrix of the oil palm plantation area were extracted and listed in Table 2. As can be seen in Figure 5, the shape of the polarisation signature was well-preserved for each test window size. Moreover, all the extracted values from the filtered outputs were close to those extracted from the unfiltered data. However, the values of \( \langle |S_{HH}|^2 \rangle, \langle |S_{VV}|^2 \rangle \) and \( \langle \Re(S_{HH}S_{VV}^*) \rangle \) dropped gradually for the larger window sizes.

To examine the preservation of point-like textural features, the coefficient of variation (CoV) of a heterogeneous area was computed from the total power output and listed in Table 1. The selected heterogeneous area was depicted by the yellow-coloured rectangle in Figure 3. By observing Figure 3, it is evident that the heterogeneous area was still preserved after filtering, but the computed CoV values were not perfectly preserved as can be seen in Table 1.

In dealing with the structural feature retention, the contrast between a structural feature and its neighbouring background was studied. In this case, the contrast \( |f| \) is defined by the absolute difference of the average total power between the selected structural feature and its neighbouring background. The higher the contrast value, the better the retention. The structural feature identified in this test was a road segment, which is located at the top of Figure 3(a). From the obtained results, the proposed filtering approach performed well in retaining the road segment. The contrast values, as tabulated in Table 1, were high for all test window sizes, but a slight performance decrease can be observed for larger sizes.

To study the effects of the proposed filtering approach on the Cloude-Pottier target decomposition parameters, the entropy, anisotropy and alpha-angle were computed from both unfiltered and filtered POLSAR data. Figure 6 shows the extracted decomposition parameters of four different land cover classes. The selected land cover samples included mangrove forest, river, oil palm and rubber plantation areas. The obtained results are identical to those of Lee et al. (2006). The entropy values increased while the anisotropy decreased after filtering. For the alpha-angle, only minor fluctuations in degree occurred as in Figure 6(c).

4. CONCLUSIONS

In this paper a spatially adaptive filtering approach was introduced for multi-look POLSAR imagery. The proposed filter consists of five processing steps, namely edge detection, line detection, texture analysis, classification based on scattering mechanisms, and despeckling. Applied to the nine-look NASA/JPL POLSAR C-band data, the proposed filter exhibited a satisfactory performance in speckle removal, image feature retention as well as radiometric preservation. Moreover, the filtering effects on the Cloude-Pottier target decomposition parameters were studied, where the obtained findings are identical to those of Lee et al. (2006).

REFERENCES


Table 1: Quantitative performance evaluation of the proposed filtering approach

<table>
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<th>Unfiltered</th>
<th>3×3 window</th>
<th>5×5 window</th>
<th>7×7 window</th>
<th>9×9 window</th>
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<td>SNR</td>
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<td>5.640</td>
<td>7.775</td>
<td>9.634</td>
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<td>CoV</td>
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<td>0.351</td>
<td>0.351</td>
<td>0.357</td>
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<td></td>
<td>0.804</td>
<td>0.793</td>
<td>0.788</td>
</tr>
</tbody>
</table>

Table 2: Average of covariance matrix elements extracted from an oil palm plantation area

|           | \(\langle |S_{HH}|^2 \rangle\) | \(\langle |S_{HV}|^2 \rangle\) | \(\langle |S_{VV}|^2 \rangle\) | \(\langle \Re (S_{HH}S_{HV}^\ast) \rangle\) | \(\langle \Im (S_{HH}S_{HV}^\ast) \rangle\) | \(\langle \Re (S_{HV}S_{VV}^\ast) \rangle\) | \(\langle \Im (S_{HV}S_{VV}^\ast) \rangle\) | \(\langle \Re (S_{HH}S_{VV}^\ast) \rangle\) | \(\langle \Im (S_{HH}S_{VV}^\ast) \rangle\) |
|-----------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|
| Unfiltered | 0.258          | 0.040          | 0.273          | -0.004         | 0.001          | 0.004          | -0.001         | 0.160          | -0.022         |
| 3×3 window | 0.255          | 0.040          | 0.271          | -0.004         | 0.001          | 0.003          | 0.000          | 0.159          | -0.022         |
| 5×5 window | 0.253          | 0.039          | 0.269          | -0.004         | 0.001          | 0.003          | 0.000          | 0.158          | -0.022         |
| 7×7 window | 0.250          | 0.039          | 0.266          | -0.003         | 0.000          | 0.003          | 0.000          | 0.156          | -0.021         |
| 9×9 window | 0.248          | 0.039          | 0.264          | -0.003         | 0.000          | 0.003          | 0.000          | 0.154          | -0.021         |

Figure 3: Speckle filtering results. (a) Unfiltered NASA/JPL POLSAR C-band data with HH, HV and VV intensities displayed in the RGB colour space, (b) and (c) Proposed filter using 7×7 and 9×9 window sizes, respectively.

Figure 4: Total power surface plots of a rubber plantation area. (a) Unfiltered, (b)–(e) Proposed filter using 3×3, 5×5, 7×7 and 9×9 window sizes, respectively.

Figure 5: Co-polarisation signature plots of an oil palm plantation area. (a) Unfiltered, (b)–(e) Proposed filter using 3×3, 5×5, 7×7 and 9×9 window sizes, respectively.

Figure 6: Cloude-Pottier target decomposition results. (a)–(e) Entropy, anisotropy and alpha-angle values extracted from mangrove forest (red), river (blue), oil palm plantation area (magenta) and rubber plantation area (black).