Analysis and Evaluation of Speckle Filters for Polarimetric Synthetic Aperture Radar (PolSAR) Data

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Abstract
Synthetic Aperture Radar (SAR) data are affected by speckle noise, because of coherent integration of back scattered signals from different targets. For one-dimensional SAR data the speckle noise is already a solved problem, due to its multiplicative nature. SAR polarimetry is an extension to multidimensional data by the use of polarization wave diversity. Any speckle filter has to suppress the speckle noise while preserving the polarimetric information and the spatial information. Speckle filtering of PolSAR images remains a challenging task due to the difficulty to reduce a scatterer-dependent noise. This paper proposes a set of speckle filters which are analysed and evaluated based on different parameters. The different parameters are Mean Square Error (MSE), Peak Signal to Noise Ratio (PSNR), Mean Structural Similarity Index Measure (MSSIM), Edge Preservation Index (EPI), Equivalent Number of Looks (ENL), Bias, Standard Deviation to Mean ratio (SD/M) and ratio image mean and standard deviation.

Keywords: Synthetic Aperture Radar (SAR), Polarimetry, Polarimetric SAR (PolSAR), speckle noise.

INTRODUCTION
Synthetic Aperture Radar (SAR) is a well-established technology for remote sensing applications. As it has been extensively reported in the literature, the information that these type of systems can gather has a crucial importance for monitoring natural features and changes on the earth’s surface. SAR systems have first been employed in a single-channel configuration to obtain high spatial resolution information about the reflectivity properties of the imaged scene. The availability of multidimensional SAR systems has made possible to increase the amount of available information about the earth’s surface. In particular, Polarimetric SAR (PolSAR) [1], [2] systems emerged as an important system configuration, based on polarization diversity, as PolSAR data are sensitive to the scattering properties of the imaged scene and the geometry of the scatterers on it. The correlation structure of the different SAR images is an important source of information, specially when the quantitative retrieval of biophysical and geophysical parameters is addressed. Nowadays, there exists an extensive amount of techniques based on PolSAR data, e.g., terrain classification, surface parameter estimation, biomass estimation, etc.

The interest on PolSAR data has increased in the last years, specially after the launch of different spaceborne missions presenting polarimetric capabilities. A PolSAR system measures the scattering matrix for every resolution element or pixel. In the case of deterministic or point scatterers, this matrix determines completely the scattering process being considered. Nevertheless, in case of distributed scatterers, and due to the coherent nature of SAR systems, the scattering matrix is no longer deterministic but random due to the complexity of the scattering process. This stochastic nature of SAR data is normally referred to as speckle noise [1], [3], [4]. This Speckle noise is one of the most important problems of SAR data. In order to achieve high spatial resolution in the azimuth direction, SAR systems coherently record the back scattered signals. The speckle noise is precisely originating from this coherent nature. This component is a true scattering measurement, but as indicated, the complexity of the scattering process makes it necessary to consider it as a noise source. Consequently, the information of interest is no longer the scattering matrix, but the different moments necessary to specify completely the probability density function (pdf) of the acquired SAR data. These moments must be estimated from the measured data, or said in a different way, speckle noise must be filtered out to grant access to these statistical moments. Hence, the modeling and the characterization of the speckle noise component, its filtering and how it affects the extraction of useful information is critical for the SAR technology, specially in case of multidimensional SAR data.
As it may be deduced from everyday life, the Earth presents a heterogeneous and dynamic nature. Thus, if observed with a SAR system, this heterogeneity is translated to the SAR data. The statistical characterization and modeling of SAR data represents today an important field of research. In case of stationary areas, PolSAR data are well described by the covariance matrix [5] of stationary areas, PolSAR data are well described by the covariance matrix [5]–[7]. Hence, this matrix represents the most important observable in PolSAR data for stationary data, which must be estimated from the recorded data. To describe texture information the Gaussian model is not sufficient. In these cases, it is necessary to increase the complexity of the statistical model describing the data in order to accommodate the texture information [8]–[11].

Speckle noise filtering in PolSAR data and the consequent extraction of useful information, as it results from what has been detailed in the previous paragraph, must be considered from the point of view of a given stochastic model for the data. Hence, the design of a particular speckle noise filter is also driven by the considered model to describe the data. As described in Polariometric SAR data speckle filters, different filtering alternatives for the reduction or elimination of speckle noise in PolSAR data have been presented and validated in the related literature. The comparison of speckle noise filters has been addressed in the case of single SAR images [12], [13], but there is a clear lack of an in-depth study in the case of PolSAR images [14]–[16].

The present paper has been organised as follows: (i) Polarimetric SAR data description (ii) PolSAR data speckle noise model, speckle noise filtering principles and PolSAR data speckle filters. (iii) PolSAR data filters evaluation procedure (iv) Results and Evaluation and (v) Conclusion.

### POLARIMETRIC SAR DATA DESCRIPTION

For each resolution cell the polarimetric SAR sensor measures a $2 \times 2$ complex scattering matrix $[S]$, which relates the components of the scattered electromagnetic field with the illuminating field, for a particular polarization basis. For the linear polarization basis case

$$[S] = \begin{bmatrix} S_{hh} & S_{hv} \\ S_{vh} & S_{vv} \end{bmatrix} \quad (1)$$

where $h$ and $v$ represent the horizontal and vertical linear polarizations, respectively. $S_{pq}$ is the scattering coefficient relating the illuminating field with $q$-polarization and the received field in $p$-polarization. $[S]$ can be decomposed in an orthogonal matrix basis, yielding to the target vector’s concept [17]. For the lexicographic decomposition basis, the target vector $k$ is

$$k = [S_{hh} \ S_{hv} \ S_{vh} \ S_{vv}]^T \quad (2)$$

where $T$ indicates transpose. For the backscattering direction, due to the reciprocity theorem under the Backscatter Alignment (BSA) convention, i.e., $S_{hv} = S_{vh}$, $k$ can be simplified to

$$k = [S_{hh} \ \sqrt{2}S_{hv} \ S_{vv}]^T \quad (3)$$

where $\sqrt{2}$ is introduced to maintain the vector’s norm $|k|^2$ or span. $[S]$ characterizes completely the scattering process for deterministic scatterers. On the contrary, it fails to characterize the scattering process for distributed scatterers, i.e., random targets. For this type of scatterers, as a consequence of the random changes from pixel to pixel, the matrix $[S]$ is, therefore, random. Based on the SAR’s coherent nature, under the Gaussian scatterer assumption, $k$ can be modeled by a multivariate, complex, zero-mean, Gaussian probability density function (pdf) [6], [7]

$$p_k(k) = \frac{1}{\pi ||[C]||} \exp (-k^\dagger [C]^{-1} k) \quad (4)$$

where $\dagger$ represents the transpose complex conjugate of a vector, and $||[C]||$ denotes the determinant of $[C]$. This pdf is completely determined by the $3 \times 3$ complex, Hermitian, covariance matrix $[C]$, defined as

$$[C] = E\{kk^\dagger\} = \begin{bmatrix} \frac{1}{2}E\{|S_{hh}|^2\} & \sqrt{2}E\{S_{hh}S_{hv}^*\} & E\{S_{hh}S_{vh}^*\} \\ \sqrt{2}E\{S_{hv}S_{hh}^*\} & 2E\{|S_{hv}|^2\} & \sqrt{2}E\{S_{hv}S_{vv}^*\} \\ E\{S_{vh}S_{hh}^*\} & \sqrt{2}E\{S_{vh}S_{vv}^*\} & E\{|S_{vv}|^2\} \end{bmatrix} \quad (5)$$

where $E\{\cdot\}$ represents the ensemble average, and $^*$ is the complex conjugate of a complex quantity. Most of natural scenes are considered as distributed scatterers; therefore, they are completely determined, in polarimetric terms, by $[C]$ and not by $[S]$. For distributed scatterers, $[S]$ has five independent parameters, whereas $[C]$ has nine. This difference comes from the fact that $[C]$ contains information concerning the data’s correlation structure. Assuming statistical ergodicity and homogeneity, can be estimated substituting the ensemble average by spatial averaging, known as multilook
that can also be expressed as
\[ S_p S_q^\dagger = \psi |\rho| \exp(j\phi_x) \]
\[ + \psi \bar{z}_n N_c (1 - n_m) \exp(j\phi_x) \]
\[ + \psi (n_{ar} + jn_{ai}) \quad (10) \]

The following list details the different parameters of the model.

i. \( \psi \) represents the average power in the two channels
\[ \psi = \sqrt{E \{ |S_p|^2 \} E \{ |S_q|^2 \}} \quad (11) \]

ii. \( |\rho| \exp(j\phi_x) \) is the complex correlation coefficient that characterizes the correlation among the channels \( S_p \) and \( S_q \)
\[ \rho = |\rho| \exp(j\phi_x) \]
\[ \frac{E \{ S_p S_q^\dagger \}}{\sqrt{E \{ |S_p|^2 \} E \{ |S_q|^2 \}}} \quad (12) \]

The amplitude of the complex correlation coefficients is normally referred to as coherence.

iii. \( N_c \) takes the expression
\[ N_c = \frac{\pi}{4} |\rho| 2 F_1 \left( \frac{1}{2}; \frac{1}{2}; 2; |\rho|^2 \right) \quad (13) \]
where \( 2 F_1(a, b; c; z) \) is the Gauss hypergeometric function. This parameter contains the same information as the coherence.

iv. \( z_n \) consists of the normalized Hermitian product amplitude
\[ z_n = \frac{E \{ |S_p S_q^\dagger| \}}{\psi} \quad (14) \]

v. \( n_m \) is the first speckle noise component characterized for presenting a multiplicative noise behaviour with respect to the information of interest. This noise component presents the following first- and second-order moments:
\[ E \{ n_m \} = 1 \quad (15) \]
\[ \text{var} \{ n_m \} = 1 \quad (16) \]

vi. \( n_{ar} + jn_{ai} \) is the second complex speckle noise component presenting an additive nature with respect to the information of interest. The components are characterized by
\[ E \{ n_{ar} \} = E \{ n_{ai} \} = 0 \quad (17) \]
\[ \text{var} \{ n_{ar} \} = \text{var} \{ n_{ai} \} = \frac{1}{2} (1 - |\rho|^2)^{1.32} \quad (18) \]
Equation (9) states that, for the complex Hermitian product of two SAR images, speckle results from the combination of the multiplicative speckle noise component \( n_m \) and the complex additive speckle noise component \( n_a + jn_{ai} \). The combination of these noise components is determined by the complex correlation coefficient (12). This parameter must be considered for a correct use of the model (9) when filtering the multiplicative and the additive speckle noise components, in such a way that the better the estimation of the complex coherence, the better the filtering.

B. Polarimetric SAR Speckle Filtering Principles

The goal of any PolSAR speckle filter to be defined must be the achievement of the requirements specified above. Several works have addressed the need to specify the general principles of a PolSAR speckle filter and which are the potential limitations: Touzi et al. [18], by Lee et al. [20] and C. López-Martínez et al. [21].

In all three cases, the information to retrieve is on the second order moments of the multidimensional SAR data. In [18], the authors propose the use of the Mueller matrix, despite they also consider the covariance matrix. In [20] and [21], the authors propose also the use of the covariance matrix. The use of the coherency matrix could be also considered [17], as the Mueller, the covariance and the coherency matrices are related by similarity transformations. Implicitly, the authors are considering that these matrices contain all the necessary information to characterize the multidimensional SAR data. This assumption is only valid under the hypothesis of (4), that only applies in case of stationary data. The presumption of more evolved stochastic data models, that may take into account additional signal variability, as for instance texture, are always associated with the need to estimate additional stochastic moments. A particular point that must be highlighted, with respect to what has been indicated above, is that a comparison of a set of PolSAR filtering techniques must be performed according to a common stochastic data model for the data. A comparison of filtering approaches based on different signal models should be carefully addressed.

Another point in which all the previous three works are in agreement is the need to perform the estimation of the previous matrices locally, adapting to the stationarity or homogeneity of the SAR data. This requirement should be justified from two different points of view. The first one refers, due to the stationarity of PolSAR data, to the need of maintaining the spatial resolution and the radiometric amplitude in case of point scatterers, which may be extended to the idea of preserving spatial details. The second refers to the fact that in case of distributed scatterers, the covariance matrix must be estimated on stationary data, avoiding the mixture of different stationary areas leading to corrupted information. This corresponds to a first level of adaptation the PolSAR filter should achieve, i.e., adaptation to the signal morphology. The approaches presented by Lee [20] clearly highlight this need. The way to adapt to the signal stationarity is based only on the diagonal elements of the covariance matrix, that contain only the radiometric information. This strategy for both locally estimating the optimal image morphology and the spatial support of the Maximum Likelihood Estimation (MLE), i.e., maximizing the number of stationary pixels, has been explored and refined by many authors.

The differences between the filtering principles for PolSAR data proposed by [18],[20],[21] are on how to consider the information that may be provided by the off-diagonal elements of the covariance matrix, and whether this information may be employed to optimize speckle noise reduction or not. The approaches proposed by [18] and [20] suggest an extension of the multiplicative speckle noise model, that applies for the diagonal entries of the covariance matrix, to the off-diagonal ones, despite it is also admitted that this extension may not lead to an optimum filtering of the speckle noise component. In [20], the authors even proposed that the use of the degree of statistical independence between elements must be avoided in order to avoid crosstalk, and that all the elements of the covariance matrix must be filtered by the same amount. These principles were extended in [21], based on a more accurate PolSAR speckle noise model for the off-diagonal elements of the covariance matrix [19]. This model predicts that for a given off-diagonal element of the covariance matrix, speckle presents a complex additive nature for low coherence values, whereas speckle tends to be multiplicative in case of high coherence. Consequently, optimum speckle noise reduction should adapt to the type of noise for the off-diagonal elements of the covariance matrix. This behavior of the data points to a second level of adaptation which is related to the preservation of the entire coherency/covariance matrix.

C. Polarimetric SAR Data Speckle Filters

The main objective of the present work is to provide a comparative study of PolSAR speckle noise filters with the intention to find the strengths of the different approaches, in order to increase the knowledge about PolSAR speckle filtering. In the following, the filtering approaches that have been considered are listed. The objective is not to provide the details of every technique, but just the filtering principle on which the filtering is based on, as details must be found in the different references. The list is as follows:

- Multilook or Boxcar filter: Corresponds to the MLE of the covariance or coherency matrices, under the hypothesis of (4) [5]. This blind low-pass
filter achieves radiometric resolution and filtering at the cost of degrading the spatial resolution and the spatial details, proportionally to the number of averaged samples or looks.

- **Lee Sigma[22]:** This filter is based on the sigma probability of a Gaussian distribution. It filters the image noise by averaging only those pixels within the two-sigma range of the center pixel within a scanning window. It is well known that the two sigma probability of Gaussian distribution is 0.955. Pixels outside the two sigma range are ignored, because they are considered as outliers. Consequently, high contrast features are preserved. However, dark spot noise is not removed from the SAR image. This is due to the small sigma range associated with the dark pixels of the multiplicative noise model, and as a result no filtering action is taken for such pixels.

- **Refined Lee Filter [20]:** The minimization of the Mean Square Error (MSE) was proposed to filter the diagonal elements of the covariance or coherency matrices [24], that was extended in [25] to include also the off-diagonal elements. In both cases, the MSE was minimized locally within a square moving window. In [20], the Refined Lee Filter considers a Local Linear Minimum Mean Square Error (LLMMSE) estimation within edge aligned windows, achieving a better preservation of the image details.

- **Lopez Filter:** In [19], speckle noise model for the complete covariance matrix in PolSAR is proposed. This speckle noise model allows to identify the noise characteristics for all the covariance matrix elements. The speckle noise characteristics depend on the complex correlation coefficient, causing the speckle noise nature to vary according to it. Two clear noise mechanisms have been identified. First of all, a multiplicative noise mechanism controlled by the real and imaginary parts of the complex correlation coefficient. This mechanism is dominant only when the real or imaginary parts of the complex correlation coefficient are close to one. The second mechanism has an additive nature, being dominant for low-coherence values. As a result, speckle noise for the off-diagonal covariance matrix elements is nonstationary, but also speckle characteristics vary between its real and imaginary parts.

- **Intensity-driven adaptive-neighborhood (IDAN):** In [23], the authors extended the ideas of [20]. Instead of employing edged aligned windows, a set of stationary pixels surrounding the pixel under analysis, adapting to the local morphology of the data is defined. As in [20], the filtering process considers only the information provided by the diagonal elements of the covariance or coherency matrices to determine stationary pixels. The search process of the stationary neighborhood is started by a seed pixel derived from the $3 \times 3$ median values of the diagonal elements. The estimated value of the covariance or coherency matrix is obtained through the mean value of the pixels within the adaptive neighborhood.

According to [26], polarimetric speckle filters are designed to achieve optimality in the retrieval of the morphological and the polarimetric information. Consequently, one may identify a first family of filtering techniques which are based on the optimization of the support to estimate the information of interest, and which final objective is to adapt to the data morphology in order to maintain the spatial resolution and to avoid the mixture of information. A second family of filters can be considered to be composed with those focused on the maintenance of the polarimetric information on the basis of considering the local statistics, or a speckle noise model, to optimize speckle noise reduction. The separation between first and second families is not strict, as some of the filtering techniques could be assigned to both families at the same time.

**POLARIMETRIC SAR DATA FILTERS EVALUATION PROCEDURE**

In general, a good SAR despeckling technique should have the following characteristics [27] and [28] (i) speckle reduction in homogeneous areas, (ii) scene feature preservation (such as texture, edges, point target, and urban areas), (iii) radiometric preservation and (iv) absence of artifacts. To assess the capacity of a filter to achieve such results, a set of suitable measures are used in the literature, which can be classified as no-reference measures (applied on real-world SAR images) and full-reference measures (when a reference SAR image is generated by simulation). Full-reference measures include Mean Square Error (MSE), Peak Signal to Noise Ratio (PSNR), Mean Structural Similarity Index Measure (MSSIM) and Edge Preservation Index (EPI). No-reference measures include Equivalent Number of Looks (ENL), Bias, Standard Deviation to Mean ratio (SD/M) and ratio image mean and standard deviation.

**Mean Square Error (MSE)**

Mean Square Error is defined as

$$MSE(x, \hat{x}) = E[(x - \hat{x})^2]$$

where $x$ and $\hat{x}$ represents original and filtered images respectively, $E[\cdot]$ denotes statistical mean. The highest value of MSE represents original and filtered images are dissimilar.
and lowest value represents better image quality of the filtered image. MSE based measurements are useful to obtain a global performance assessment on the whole image, but usually they yields little information about the preservation of specific features, for which other indexes can be used.

**Peak Signal to Noise Ratio (PSNR)**

This parameter represents the ratio between the maximum possible power of the original and the noise image which can be obtained as

\[
PSNR = 10 \log_{10} \left( \frac{x_{PEAK}^2}{MSE} \right)
\]  
(20)

here \(x_{PEAK}\) represents maximum value allowed by the samples dynamic range. Better filtered image quality is indicated by a higher PSNR value.

**Mean Structural Similarity Index Measure (MSSIM)**

The mean structural similarity index measurement (MSSIM) was proposed in general for denoising framework and adopted also in the context of despeckling, which represents changes in structural information after the filtering process. MSSIM takes values over the interval \([0,1]\), where 0 and 1 indicate no structural similarity and perfect similarity, respectively.

\[
MSSIM = \frac{1}{M} \sum_{p=0}^{M-1} \frac{2E[x_p]E[\hat{x}_p] + C_1}{E[x_p^2] + E[\hat{x}_p^2] + C_1} \frac{2Cov[x_p, \hat{x}_p] + C_2}{Var[x_p] + Var[\hat{x}_p] + C_2}
\]  
(21)

where \(x_p, \hat{x}_p, p = 0, \ldots, M - 1\) are original and filtered image patches. \(C_1\) and \(C_2\) are suitable constants.

**Edge Preservation Index (EPI)**

Edge Preservation Index is defined as follows

\[
EPI = \frac{\sum_{i=1}^{n} |\hat{x}_{i,1} - \hat{x}_{i,2}|}{\sum_{i=1}^{n} |x_{i,1} - x_{i,2}|}
\]  
(22)

where \(x_{i,1}, x_{i,2}, \hat{x}_{i,1}\) and \(\hat{x}_{i,2}\) are the values of the original and filtered images, respectively, observed on the one-pixel wide lines on both sides of the edge. Larger values correspond to a better edge retaining ability of the filter.

**Standard Deviation to Mean ratio (SD/M)**

This is also called as Coefficient of Variation (CV) which is well known quantitative measure for evaluating the level of smoothing in homogenous area. Lower values of CV represents good speckle noise reduction.
**Figure 1:** Original Pauli RGB of (a) San Francisco and (b) Ottawa.

**Figure 2:** Comparison of speckle filtering using AIRSIR L-band PolSAR data (a) Original Pauli RGB, (b) $3 \times 3$ Boxcar, (c) $7 \times 7$ Lee Sigma, (d) $3 \times 3$ Refined Lee, (e) $3 \times 3$ Lopez, (f) IDAN.
The following list details the parameters that have been employed for every PolSAR filter: (i) Multilook or Boxcar filter: This filter has been tested considering windows of 3 × 3, 5 × 5, 7 × 7 and 9 × 9-pixel windows. (ii) Lee Sigma filter: This filter is tested considering a 7 × 7, 9 × 9 and 11 × 11-pixel window. (iii) Refined Lee filter: This filter is evaluated considering 3 × 3, 5 × 5, 7 × 7 and 9 × 9-pixel windows. (iv) Lopez filter: This filter is evaluated considering 3 × 3, 5 × 5 and 7 × 7-pixel windows. (v) IDAN filter: The filter is tested considering a maximum region size of 80 pixels.

The observation of Fig. 2 and Fig. 3 details the capability of the different filtering approaches to preserve the spatial resolution and the spatial details. The Boxcar filtering approach degrades spatial resolution due to the absence of internal mechanism to preserve spatial resolution or spatial details. The rest of the filtering approaches include such a mechanism. The preservation of spatial resolution and spatial details is basically addressed locally, by trying to adapt to the data morphology. The family of Lee filters adopt a scheme based on the use of aligned windows together with a LMMSE. The Refined Lee approach uses directional windows together with a LMMSE, resulting into a better preservation of the spatial resolution and the spatial details when compared to Lee Sigma filter, but smoothing effect is still noticeable on the filtered data using Refined Lee. Lopez filter processing is based on multilook. Multilook results into a relatively correct maintenance of the spatial resolution and spatial details but into biased information which can be observed from Table I and Table II. If the iterated multilook process is used then the maintenance of the spatial details is poor but a correct statistical estimation is possible.
### Table I. Quantitative comparison of different speckle filters using AIRSAR L-band data.

<table>
<thead>
<tr>
<th>Filter / Parameter</th>
<th>MSE</th>
<th>PSNR</th>
<th>MSSIM</th>
<th>EPI</th>
<th>SD/M</th>
<th>ENL</th>
<th>Bias</th>
</tr>
</thead>
<tbody>
<tr>
<td>Boxcar3</td>
<td>172.4982</td>
<td>25.7630</td>
<td>0.4148</td>
<td>0.3598</td>
<td>0.6166</td>
<td>2.6304</td>
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<td>Boxcar5</td>
<td>184.8671</td>
<td>25.4622</td>
<td>0.2417</td>
<td>0.2073</td>
<td>0.6084</td>
<td>2.7016</td>
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<td>189.0758</td>
<td>25.3644</td>
<td>0.1828</td>
<td>0.1486</td>
<td>0.6023</td>
<td>2.7569</td>
<td>0.0949</td>
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<td>Boxcar9</td>
<td>191.0959</td>
<td>25.3183</td>
<td>0.1696</td>
<td>0.1107</td>
<td>0.5970</td>
<td>2.8059</td>
<td>0.0959</td>
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<tr>
<td>Lee Sigma7</td>
<td>176.7003</td>
<td>25.6584</td>
<td>0.3789</td>
<td>0.2269</td>
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<td>0.2417</td>
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<td>Refined Lee3</td>
<td>164.1490</td>
<td>25.6450</td>
<td>0.3845</td>
<td>0.2161</td>
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<td>0.3327</td>
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<td>Refined Lee7</td>
<td>184.1467</td>
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<td>0.4525</td>
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<td>25.6450</td>
<td>0.3866</td>
<td>0.2133</td>
<td>0.6133</td>
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<td>Lopez3</td>
<td>172.4406</td>
<td>25.7644</td>
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<td>26.0323</td>
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<td>0.5437</td>
<td>0.6154</td>
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* Bold indicates better value/performance

### Table II. Quantitative comparison of different speckle filters using CONVAIR C-band data.

<table>
<thead>
<tr>
<th>Filter / Parameter</th>
<th>MSE</th>
<th>PSNR</th>
<th>MSSIM</th>
<th>EPI</th>
<th>SD/M</th>
<th>ENL</th>
<th>Bias</th>
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<td>0.4808</td>
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<td>4.0539</td>
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<td>24.9487</td>
<td>0.2816</td>
<td>0.3175</td>
<td>0.5339</td>
<td>3.5076</td>
<td>0.1270</td>
</tr>
<tr>
<td>Boxcar7</td>
<td>218.8653</td>
<td>24.7290</td>
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</tbody>
</table>

* Bold indicates better value/performance
Table III. Quantitative comparison of different speckle filters using ratio image.

<table>
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<tr>
<th>Filter / Parameter</th>
<th>San Francisco Image</th>
<th>Ottawa Image</th>
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<td><strong>0.5508</strong></td>
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</tbody>
</table>

* Bold indicates better value/performance

The spatial strategy was improved by the IDAN approach, that as observed, performs a good preservation of spatial resolution and details, despite that some of them are clearly smoothed. This filtering approach results into a degradation of the radiometric information. Visual inspection also shows that some details of the image are clearly narrower.

The quantitative analysis of these filters are given in Table I, Table II and Table III. In Table I and Table II Mean Square Error (MSE), Peak Signal to Noise Ratio (PSNR), Mean Structural Similarity Index Measure (MSSIM), Edge Preservation Index (EPI), Equivalent Number of Looks (ENL), Bias and Standard Deviation to Mean ratio (SD/M) are compared with AIRSAR L-band and CONVAIR C-band PolSAR data respectively. In Table III mean and standard deviation of the ratio images of both the date sets are compared.

The data in Table I shown for AIRSAR L-band PolSAR data, the IDAN filter has lowest MSE of 162.1267 and lowest Bias of 0.0666. IDAN filter has highest PSNR of 26.0323, highest MSSIM of 0.5827 and highest EPI of 0.5437. The Lopez with 7 × 7 window has lowest SD/M of 0.5955 and highest ENL of 2.8197. From Table II with CONVAIR C-band PolSAR data, IDAN filter has lowest MSE, SD/M and Bias of values 174.3357, 0.4727 and 0.0444 respectively. IDAN filter has highest PSNR, MSSIM and EPI of values 25.7369, 0.6039 and 0.6266 respectively. The Lee Sigma filter with 11 × 11 window has highest value of ENL which is 4.9526. Table III, shows that Boxcar filter with 3 × 3 window is having the mean value of 1.0053 close to one and IDAN filter has minimum standard deviation of 0.5508 for AIRSAR L-band PolSAR data. For CONVAIR C-band PolSAR data the mean value of Lee Sigma filter with 7 × 7 window is close to one which is 0.9788 and standard deviation is minimum for IDAN filter which is 1.1919.

CONCLUSION

From the visual interpretation and quantitative comparison the Boxcar filter reduces speckle but plenty of details are missing due to blurring. Blurring increases with the window size since it has no internal mechanism to preserve the spatial details. In case of Lee Sigma and Refined Lee the restoration of spatial details is achieved compared to Boxcar. As the window size is increased in both the filters,
some details may overly enhanced and also brings in some block effect. The Lopez filter has good spatial detail preservation at the cost of introducing bias. As the number of iterations increases it shows poor spatial detail preservation but good statistical estimation. The IDAN filter uses Adaptive Neighborhoods as spatial support, derived with respect to the intensity information. Due to which the speckle noise is greatly reduced, while the contours and fine details are preserved and the blurring effect is avoided. The general conclusion is that the choice of the filtering algorithm to be used on PolSAR data set still remains application specific. The IDAN filter is a good compromise between variance or bias reduction and preservation of the spatial resolution, which makes it very useful for automatic unsupervised activities (edge detection, segmentation or automatic classification).

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REFERENCES


