Speckle Modeling and Turbo Filtering of PolSAR Images

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Key words: POLSAR images, speckle modeling, specklefiltering, Turbofilter, refinedLee filter, wavelet filtering, SWT

SUMMARY

SAR polarimetric radar imagesare affected byagranular noisecalledspeckle, which degrades the qualityof these images andmakesit difficult to interpret. That is why apolarimetricfilteringis essential. Thediagonal terms of thecovariance matrixCrepresent the intensityofthelinear polarization andcan be characterized byamultiplicative noise. Theoff-diagonal terms containanoisethat cannot becharacterized by amultiplicativeoradditive model.

In this paper,we are interested inmodeling thespeckle in theoff-diagonalterms ofthe covariance matrix *C*andfilter thesetermswith adjusting thefiltering methodalready developedforthe diagonalterms.Therefore, ourobjective is to adaptthe filtering methodcalledTurbo to filter PolSAR images containingnoisethatis notmultiplicativeoradditive. The principle ofTurbofilter is that itcombines two complementary filters: the refined Leefiltering based on the estimation of the minimum mean square error MMSE andthewaveletfiltering by using the stationary wavelet transform SWT. One filter can boost up the results of the other. We proposeto optimizethis methodby addinga parameter in the calculation of the threshold inthewaveletfiltering using multi-scale edge detection and thetechnique for improving thewavelet coefficients calledSSC (sum of squared coefficients), this parameter will controlthefiltering effect and geta good compromise betweensmoothinghomogeneous areasand preserving linear structures. The advantage of this algorithm is to use the advantages of both filters and to obtain images with well reduced speckleandfilteralltheelementsofthe covariance matrix, taking into account the noise typeofeachcomponent.

Visualandstatistical evaluationand acomparative study are performed tovalidate theobtained results according to the following criteria: best filtering in terms of smoothing homogeneous areas, preserving edges and conservation of the polarimetric information.

RÉSUMÉ

Les images radar SAR polarimétriques sont affectées par un bruit granulaire appelé speckle qui dégrade la qualité de ces images et rend difficile leur interprétation. C'est pour cela qu'un filtrage polarimétrique est primordial. Les termes diagonaux de la matrice de covariance *C* représentent l'intensité de la polarisation linéaire et peuvent être caractérisés par un bruit multiplicatif. Les termes hors-diagonaux contiennent un bruit qui ne peut être caractérisé ni par un modèle multiplicatif ni additif.

Dans cette communication, nous nous intéressons à la modélisation du speckle dans les termes hors diagonaux de la matrice de covariance et de filtrer ces termes tout en leur adaptant la méthode de filtrage déjà élaboré pour filtrer les termes diagonaux caractérisées par un bruit multiplicatif. Donc, notre objectifest d'adapter la méthode de filtrage appelée Turbo pour filtrer les images PolSAR contenant un bruit qui n'est ni multiplicatif ni additif. Le principe du filtre Turbo est qu'il combine deux filtres complémentaires: le filtrage de Lee adaptatif basé sur l'estimation de l'erreur quadratique moyenne minimale (MMSE : Minimum Mean Square Estimation) et le filtrage en ondelettes en utilisant la transformée en ondelettes stationnaire SWT. Chaque filtrepeut booster les résultats de l'autre. Nous proposons d'optimiser cette méthode en rajoutant un paramètre au niveau du calcul du seuil dans le filtrage par les ondelettesen utilisant la détection de bords multi-échelles et la technique d'amélioration des coefficients d'ondelettes appelée SSC (Sum of Squared Coefficients), ce paramètre permettra de mieux contrôler l'effet du filtrage et d'obtenir un bon compromis entre le lissage des zones homogènes et la préservation des structures linéaires. L'intérêt de cet algorithme est d'utiliser les avantages des deux filtres et d'obtenir des images avec un speckle bien réduit ainsi que de filtrer tout les éléments de la matrice de covariance tout en prenant en considération le type de bruit de chaque composante.

Une évaluation statistique et visuelle, ainsi qu'une étude comparative sont effectuées pour valider les résultats obtenus, selon les critères suivants : meilleur filtrage du point de vue lissage des zones homogènes, préservation des contours et conservation de l'information polarimétrique.

Mots clé : Images POLSAR, Modelisation speckle, Filtre Turbo, Filtre de Lee, Filtre Ondelettes,

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1. INTRODUCTION

PolSAR radar imagery has the advantage, compared to optical imaging, can acquire data at night and under cloud cover. However, PolSAR images contain a specific noise called speckle. This noise impairs the readability of the radar images and is often the main cause of processing failure algorithms and information extraction. Also, many studies have been devoted to filtering these data to reduce speckle (Novaket al., 1990) (Lee et al., 1999) (Farage et al., 2007) (Alonso-Gonzálezet al., 2013).

In this paper, we studied the specklenoise modeling inall elements ofthe covariance matrixC(Leeet al., 2009) andwe noticed thatthese elements do notcontain the samenoise type i.e. multiplicative noise and thatbasedon the work ofLee(Leeet al., 1999)andLópez-Martínez(López-Martínezet al., 2003). And we alsostudied thefilteringmethoddevelopedto treat thesecomponentsthat do not containmultiplicative noise unlike most methods,so we usedtheTurbo filteringfor polarimetric SAR imagesproposed byFarage(Farageet al., 2008)to filterthe diagonal elements ofthe covariance matrixin a mannerand theotherelementsotherwise byadaptingthe filter relationshipin order to treatanoisewhich is neitheradditivenormutiplicatif.This method combines the refined Lee filter (Lee et al., 1999) with filtering by stationary wavelet transform SWT (Farage et al., 2007). Refined Lee filter is based on the estimation of the minimum mean square error MMSE in the detected aligned edges. Wavelet filtering applied the stationary wavelet transform SWT on noisy images using multi-scale edge detection and sum of squared coefficients SSC technique for the wavelet coefficients improvement.

We propose to optimize this method by adding a parameter in the calculation of the threshold in the wavelet filtering, this parameter will better control the filtering effect and get a good compromise between smoothing homogeneous areas and preserving edges. The purpose of the Turbo algorithm is to use the advantages of both filters and to obtain images with well reduced speckle. Its principle is that each filter can boost the results of the other. We have implemented this new method and compared the results with those of the twofiltersalready developed, refined Lee filter and SWT filtering (Bouchemakh et al., 2008) (Boutarfa et al., 2010). And that, in order to determine its effectiveness in speckle reducing, according to the following criteria: best filtering in terms of smoothing homogeneous areas, preserving edges and conservation of the polarimetric information.

Two evaluation areas were considered in this study, image corresponding of Oberpfaffenhofen area located in Munich (Germany) in P-band airborne polarimetric mode (E-SAR) and image of an area located in Algiers (Algeria) in C-band spaceborne polarimetric mode (RADARSAT-2).

2. SPECKLE MODELING

The speckle model inpolarimetricradar imagesisa multiplicative model(Lee, 1980)(Lee,1981), represented by:

$$y = v \times x \text{ with } (\sigma_v)^2 = \frac{1}{L} \text{ and } C_v = \frac{\sigma_v}{< v >} \qquad (1)$$

Where y is the original pixel of the observed signal, x is the filtered pixel that corresponds to the information that can be measured and v is therandom process related to the speckle noise, which is multiplied to the signal, with a mean value $< v > = 1$, L is the number of look, $(\sigma_v)^2$ is the speckle variance and C_v is the coefficient of variation of the speckle . The filtering purpose is to estimate the pixel $x$knowing the observed pixel y.

The polarimetric filtering reduces the speckle in the elements of the covariance matrix$C$(eq.2) or the coherencymatrix$T$(Leeet al., 2009).Thediagonal terms of thecovariance matrix$C$represent the intensityofthelinear polarization andcan be characterized byamultiplicative noise. Theoff-diagonal terms containanoisethat cannot becharacterized by amultiplicativeoradditive model(Leeet al., 1999).

In our study, we used the polarimetric covariance matrix$C$in the monostatic casewhich is written as follows:

$$(2) \qquad C = \begin{pmatrix} |HH|^2 & HH.HV^* & HH.VV^* \\ HV.HH^* & |HV|^2 & HV.VV^* \\ VV.HH^* & VV.HV^* & |VV|^2 \end{pmatrix}$$

Where the superscript "*" refers to the complex conjugate

López-Martínezhave developed a new formulation of the noise model in the off-diagonal images(López-Martínez et al., 2003). They demonstrated that these images are affected by a noise resulting from an addition of two noise types, multiplicative and additive, as shown in the following expression :

$$HH \cdot VV^* = \underbrace{\psi N_C \bar{z}_{nor} n_m e^{j\phi_x}}_{Multiplicatif\ Term} + \underbrace{\psi\left(|\rho| - N_C \bar{z}_{nor}\right)e^{j\phi_x} + \psi\left(n_{ar} + jn_{ai}\right)}_{Additif\ Term}$$

$$\text{with } \psi = E\left\{|HH|^2\right\} \text{ and } N_C = \frac{\pi}{4}\, {}_2F_1\left(\frac{1}{2}, \frac{1}{2}; 2; |\rho|^2\right) \qquad (3)$$

where Eisthe expected value, ${}_2F_1$is the Gauss hypergeometric function, $N_C$is afunction of$|\rho|$, $\bar{z}_{nor}$is the normalised amplitude of the Hermitian product, $n_m$is the multiplicatif noise, ρ is the coefficient of correlation, ϕ_x is the phasevalue, n_{ar} and n_{ai} areadditive noise terms.

3. TURBO FILTER

A new approach tospecklereductioninpolarimetricradar SARimagesbased on theiterativeturboprincipleis proposed by Farage (Farageet al., 2008). The Turbofilteringis a combination oftwocomplementaryfilters, each of the two filterscan boostthe results ofthe otherby processing its residueimageand retrievinguseful information.Some filters, such as refined Leefilter (Leeet al., 1999), tend to getavery smooth imageand otherfilters, such as waveletfiltering (Farageet al., 2007), tend to keep structural information, leaving some noisein theestimated image. Therefore,the interest of theTurboalgorithmis to usethe advantages of bothfilters.We proposeto optimizethis methodby addinga parameterin the calculationof the threshold inthewaveletfiltering, this parameter will controlthe filtering effect and geta good compromise betweensmoothinghomogeneous areasand preservinglinear structures.

4. FILTERING BY WAVELET TRANSFORM

Wavelets are an effective tool for image processing applications. They can identify and analyze the discontinuities in the image at different levels. This property is used for filtering the wavelet coefficients before making the image reconstruction.

In what follows, we first recall the principle of the used wavelet transform, then we consider the principle of filtering by multi-scale edge detection and coefficients thresholding. The input imageI_n used in the following sections is defined by:

$$I_n = \begin{bmatrix} |HH|^2, |HV|^2, |VV|^2, \Re\{HH\}, \Re\{HV\}, \Re\{VV\}, \Im\{HH\}, \Im\{HV\}, \Im\{VV\}, \\ |HH \cdot HV*|^2, |HH \cdot VV*|^2, |HV \cdot VV*|^2, \Re\{HH \cdot HV*\}, \Re\{HH \cdot VV*\}, \\ \Re\{HV \cdot VV*\}, \Im\{HH \cdot HV*\} \Im\{HH \cdot VV*\}, \Re\{HV \cdot VV*\} \end{bmatrix} \quad (4)$$

Where $\Re$ is the real part and $\Im$ the imaginary part of the complex image.

4.1 Stationary Wavelet Transform SWT

The wavelet transform used in the filtering method is the stationary wavelet transform SWT (Farageet al., 2007). The SWT generates four images, three high frequency images called wavelet coefficients corresponding to the horizontal, vertical and diagonal directions noted by : W_h^j, W_v^j, W_d^j, and an low-frequency image called approximate image noted by A^j, bringing the highest percentage of information content among the four images. The transformation generates an equal number of wavelet coefficients at all scales. j represents the number of scale ($j = 1, ..., J$). The SWT transform is similar to the discrete wavelet transform DWT, except that the image is not decimated and in each level decomposition, the filters are upsampled by inserting zeros between each filter coefficient. Then, details images are the same size as the original image.

4.2 Filtering by Multi-Scale Edge Detection

To provide robustness to speckle filtering, the amplitude of the operator at level j is expressed as follows (Scharcanskiet al., 2002):

$$M_n^j = \sqrt{\sum_{\varepsilon=h,v,d} \left(W_\varepsilon^j\right)^2} \qquad (5)$$

Where n is the number of the input image.

The procedure for classifying wavelet coefficients proposed by Farage(Farageet al., 2007) based on the SSC (Sum of Squared Coefficients) is given as follows:

$$g^j = \begin{cases} 1 & if \ \sum_{n=1}^{N} \left(M_n^j\right)^2 > T \\ 0 & otherwise \end{cases} \qquad (6)$$

Where N is the total number of input images and T is the estimated threshold.

The edge coefficients tend to become larger at higher scales while the noise becomes smaller. If the image structures produce very large wavelet coefficients that must be preserved (Farageet al., 2007), a thresholdis imposed as:

$$g^j = \begin{cases} 1 & if \ ECM\left\{M_n^j\right\}^{n=1,2,3} > \sqrt{L+2} \\ 0 & otherwise \end{cases} \qquad (7)$$

Where $g^j$is the binary mask at level j.ECM (Enhancement Factor Method) is the improvement wavelet coefficients method by using the PCA (Principal Component Analysis) or the SSC (Sum of Squared Coefficients).

With:

$$SSC = \sum_{n=1}^{N} \left(M_n^j\right)^2 \qquad (8)$$

Another classification method of edge and non-edge coefficients is proposed by Dachasilaruk (Dachasilaruk, 2008). It is given by:

$$g^j = \begin{cases} 1 & if \ \left(M^j\right)^2 > \sigma_v^j \\ 0 & otherwise \end{cases} \qquad (9)$$

With $$\sigma_v^j = Median\left(\left|M^j\right|^2\right) \Big/ 0.6745 \qquad (10)$$

If $g^j=1$, we have an edge and if $g^j=0$, we haven't any edges in the region.

For the calculation of σ_v^j, we propose to add in the equation (eq.10) a parameter γ which allows to control the filtering effect, therefore, to obtain a good compromise between smoothing homogeneous areas and preserving edges. The expression of σ_v^j becomes:

$$(11) \qquad \sigma_v^j = \gamma \; Median\left(\left|M^j\right|^2\right) \Big/ 0.6745$$

Once the masks are obtained, the wavelet coefficients are multiplied by the shrinkage function such as :

with (12) $\left(W_\varepsilon^j\right)' = g^j \times W_\varepsilon^j \qquad \varepsilon = h, v, d$

Through the equation (12), we obtain the new filtered coefficients $\left(W_\varepsilon^j\right)'$ that will be used in the inverse wavelet transform to obtain the filtered image.

The steps of the multi-scale edge detection filtering method are listed below:

- Apply the stationary wavelet transform SWT.
- Improve the wavelet coefficients M^jusing the SSC technique on the input images.
- Classify the edge coefficients and no-edge coefficients, using the masking (eq.9).
- Modify the wavelet coefficients by multiplying them by the mask g^j (eq.12).
- Apply the inverse wavelet transform ISWT to produce the filtered images.

5. REFINNED LEE FILTER

The refined Lee filter (Lee et al., 1999)is an adaptive filter based on the criterion of minimum mean square error MMSE (eq.13), and the calculation of statistical parameters of the image. It considers the speckle as a multiplicative noise statistically independent of the scene. The estimatedfiltered pixelby theMMSEmethod is as follows:

$$x = \bar{y} + b(y - \bar{y}) \qquad (13)$$

Where x is theestimated value of thefilteredpixel, $\bar{y}$ isthe local averageofunfiltered pixels and $b$is the adaptive filteringcoefficientwitha value between0 and 1.

6. TURBO FILTER PRINCIPLE

The idea is togenerate twocomponents$U_1$and U_2fromthe original imageI_k as shownin (Fig.1) (Farage et al., 2008).

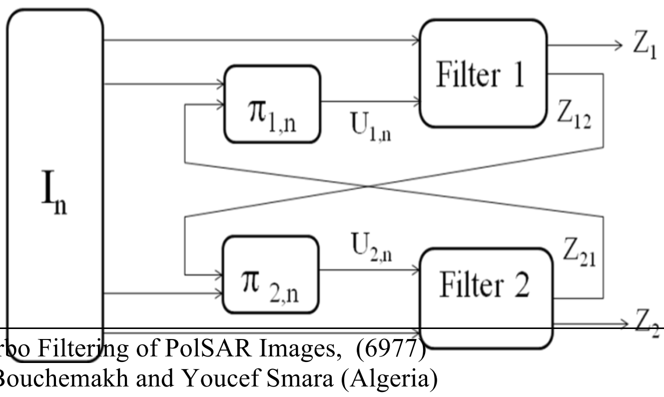


Figure 1. Diagram of Turbofilter principle.

In Figure 1, the filter 1 is the wavelet filter; the filter 2 is the refined Lee filter; the output Z_1 represents the filtered image by Turbo SSC; the output Z_2 represents the image filtered by the Turbo Lee; the two componentsU_1 and$U_2$are obtainedfromoperators$\pi_1$and$\pi_2$as follows:

$$\pi_{2,n} \overset{\Delta}{=} \begin{cases} U_{2,n} = Z_{12,n} Z_{21,n} & \text{for diagonal terms} \\ U_{2,n} = \psi_n \bar{z}_{nor,n} Z_{12,n} e^{j\phi} & \text{for off-diagonal terms} \end{cases} \tag{14}$$

$$\pi_{1,n} \overset{\Delta}{=} \begin{cases} U_{1,n} = \left| I_n / Z_{21,n} \right| & \text{for diagonal terms} \\ U_{1,n} = \left| \dfrac{I_n}{\psi_n \bar{z}_{n,k}} \right| & \text{for off-diagonal terms} \end{cases} \tag{15}$$

Wheren is theinput image number.

Twodifferent filtersare chosenin a waythat theirperformancescomplement each other.The filter1 (fig.1) should have atendency to reduce thenoise withagood edge preservation,and must treatthe noise ofresidue imagesto retrieveuseful information.The filter2 (fig.1)should result inaspeckle reduction withagood estimation of thepolarimetric parameters. The output signals Z_{12}andZ_{21}arethe exchanged information between the two filtersto equilibrate the performanceof the Turbo filter.At each iteration,$Z_{12}$and$Z_{21}$are estimatedto improve the performanceof each filterand to compensatetheir costs.The iterative processstops when change in$Z_{21}$is small.

The stepsof the Turbo filtermethod are:

− ApplySWT on the originalimageI_n forthe initialization,$Z_{21}$is the low-frequencyimageA^j.
− Calculatethe residue imageU_1fromthe operatorπ_1(eq.14) and apply the Filter1 onU_1 andI_n.
− Calculatethe residue imageU_2fromthe operatorπ_2(eq.15) and apply the Filter2onU_2 andI_n.
− Stopthe iterationswhen changeinZ_{21}becomes smallorgo to *step2*for another iteration.

7. EXPERIMENTAL RESULTS

7.1 Speckle Model Validation

In our work, according to the study of Lee et al. (Lee et al., 1999), we tested the statistical characteristics ofdiagonalandoff-diagonal termsby plotting the scatter of the standard deviation versus the mean, employing a movingwindow of size 5×5pixels of RADARSAT-2 imagescorresponding to Algiers area(Algeria).In Figure2,the intensities images $|HH|^2$, $|HV|^2$ and $|VV|^2$, showthe characteristics of amultiplicative noise. The real and imaginarypartsare more difficult tocharacterize, they showthe characteristics of anoisethat is notmultiplicative.

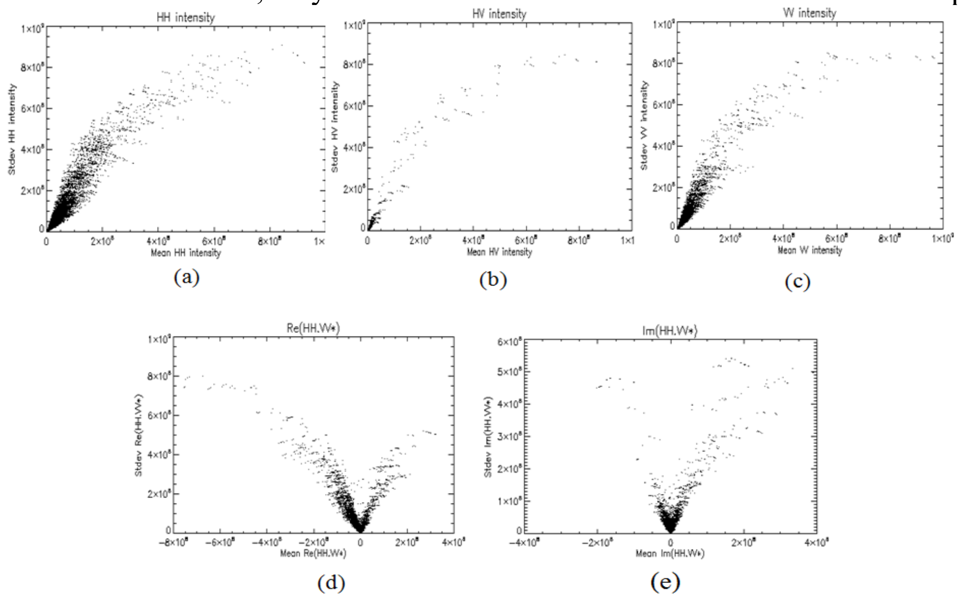


Figure 2. The scatter plotting of the standard deviation versus the mean.
(a) $|HH|^2$, (b) $|HV|^2$, (c) $|VV|^2$, (d) $\Re\{HH \cdot VV^*\}$, (e) $\Im\{HH \cdot VV^*\}$.

By using the new formulation of the noise model (eq.3) developped byLópez-Martínez(López-Martínez et al., 2003). Weplotted the scatter of the standard deviation versus the mean in both parts multiplicative and additive of the off-diagonal terms corresponding toRADARSAT-2 images of Algiers area(Algeria). Indeed, the results in figure 3 showthat theoff-diagonaltermshave a noiseresulting from a sumoftwo noise types additiveandmutltiplicative noise.

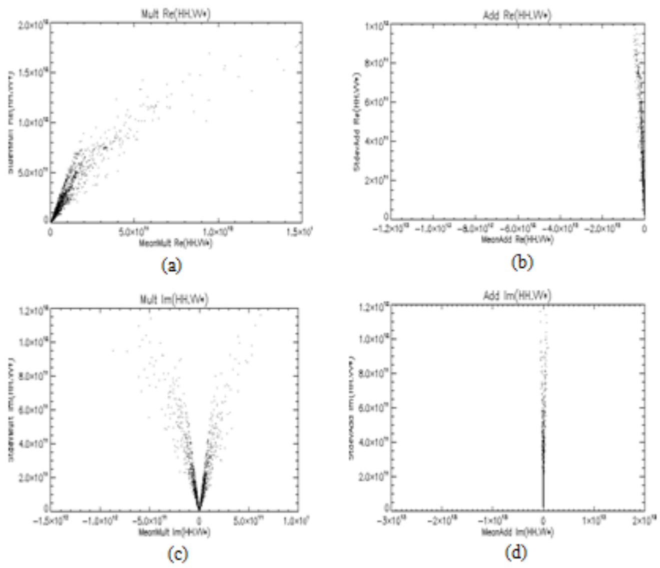


Figure 3. The scatter plotting of the standard deviation versus the mean.
(a) Multiplicative part of $\Re\{HH \cdot VV^*\}$, (b)Additve part of $\Re\{HH \cdot VV^*\}$,
(c) Multiplicative part of $\Im\{HH \cdot VV^*\}$, (d)Additve part of $\Im\{HH \cdot VV^*\}$.

The following section presents the different results obtained by the Turbo filtering considering the speckle modeling in all polarimetric covariance matrix elements.

7.2 Filtering Results

The filters tests are made on extracted images from two single-look POLSAR complex images, one is airborne corresponding to the region of Oberpfaffenhofen in Germany acquired by E-SAR sensor in 2001 (P-band) and the other corresponding to the area of Algiers in Algeria acquired by RADARSAT-2 in April 2009 (C-band). The evaluation of each filter is based on the following main criteria: Ability to smooth the homogeneous areas, ability to preserve edges and especially preserving the polarimetric information.

7.2.1 Visual Evaluation

The results are shown in (fig. 4,5) for Algiers region and (fig. 6,7) for Munich area.

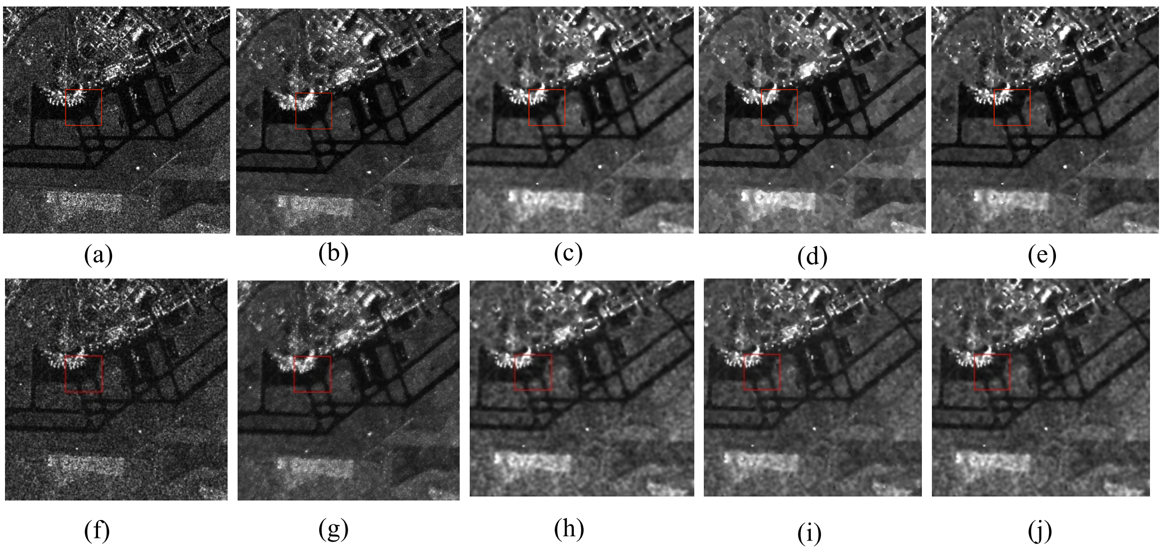


Figure 4.images of Algiers region. (a) Original*Span*, (b) Lee*Span*, (c) SSC*Span*, (d) Turbo Lee*Span*, (e) Turbo SSC*Span*,(f) Original $|HH \cdot VV^*|$, (g) Lee $|HH \cdot VV^*|$, (h) SSC $|HH \cdot VV^*|$, (i) Turbo Lee $|HH \cdot VV^*|$, (j) Turbo SSC $|HH \cdot VV^*|$.

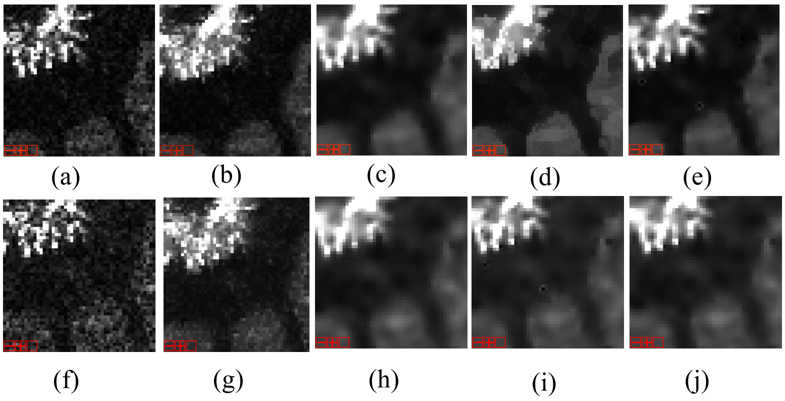


Figure 5.Zoom images of Algiers region. (a) Original *Span*, (b) Lee *Span*, (c) SSC *Span*, (d) Turbo Lee *Span*, (e) Turbo SSC *Span,* (f) Original $|HH \cdot VV^*|$, (g) Lee $|HH \cdot VV^*|$, (h) SSC$|HH \cdot VV^*|$, (i) Turbo Lee $|HH \cdot VV^*|$, (j) Turbo SSC $|HH \cdot VV^*|$.

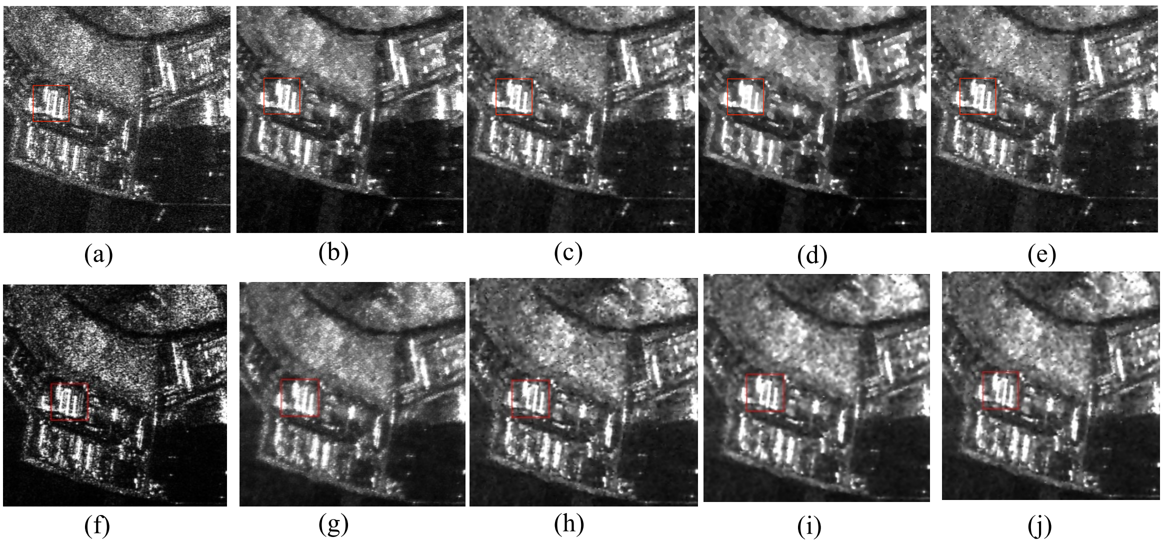
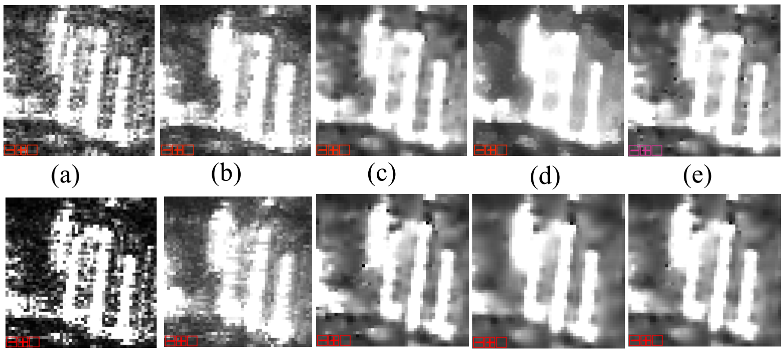


Figure 6. images of Munich region. (a) Original*Span*, (b) Lee*Span*, (c) SSC*Span*, (d) Turbo Lee*Span*, (e) Turbo SSC*Span,*(f) Original$|HH \cdot VV^*|$, (g) Lee$|HH \cdot VV^*|$,

(h) SSC $|HH \cdot VV^*|$, (i) Turbo Lee $|HH \cdot VV^*|$, (j) Turbo SSC $|HH \cdot VV^*|$.



(a) (b) (c) (d) (e)

(f) (g) (h) (i) (j)

Figure 7.Zoom images of Munich region. (a) Original *Span*, (b) Lee *Span*, (c) SSC *Span*, (d) Turbo Lee *Span*, (e) Turbo SSC *Span,* (f) Original $|HH \cdot VV^*|$, (g) Lee $|HH \cdot VV^*|$, (h) SSC $|HH \cdot VV^*|$, (i) Turbo Lee $|HH \cdot VV^*|$, (j) Turbo SSC $|HH \cdot VV^*|$.

According tothe above figures, we see that the filtered imagesbyTurboLeeare wellsmoothedand the filtered imagesbyTurboSSCpresent a good compromisebetweensmoothinghomogeneous areasand preserving linear structures, details ofobjects appearclearerthan in the otherfiltered images.

7.2.2 Statistical Evaluation

*Evaluation in Homogeneous regions:*The evaluation performance of each filterin terms ofsmoothingis performed onhomogeneous areasof size 20×20 pixels extractedfrom the imagesbefore and afterfiltering. This evaluation is done by calculatingthe equivalent numberof looksENL (Bouchemakh et al., 2008). A goodfilteringin homogeneous areasis representedby an increase value of ENL.

The statistical resultsare shownin the following table:

Table 1. ENLvaluesin *Span* images.

Areas		Original	Turbo Lee	Turbo SSC	Lee	SSC
Algiers	intensity	2.66	7.26	5.28	7.70	8.40
	SLC	0.64	1.08	1.17	3.19	3.77
Munich	intensity	2.17	16.12	11.47	8.73	18.91
	SLC	0.49	3.93	12.35	5.25	6.51

Table 2. ENLvaluesin $HH \cdot VV^*$ images.

Areas		Original	Turbo Lee	Turbo SSC	Lee	SSC
Algiers	intensity	1.07	8.56	4.53	7.00	5.50
	SLC	0.50	1.27	1.19	4.36	4.87
Munich	intensity	1.98	14.19	13.12	9.08	17.04
	SLC	0.30	3.48	14.19	4.50	7.18

From tables1 and 2, overall, the statistical evaluation of the obtained results of Turbo filter showed a great ability to preserve edges and smooth homogeneous areas. Thus, these results follow the conclusions of visual evaluation.

*Evaluation in Heterogeneous regions:*Thebest filterin terms of edgepreservation is the one givingthe highestcoefficient of variationC_{vg} (Bouchemakh et al., 2008) calculated fromthreeheterogeneous areasofsize10×10pixels.The resultsare illustratedin the following table:

Table 3. C_{vg}valuesin *Span* images.

Areas		Turbo Lee	Turbo SCC	Lee	SSC
Algiers	intensity	1.51	1.28	1.81	1.23
	SLC	0.65	0.85	1.15	1.52
Munich	intensity	0.24	0.40	0.35	0.26
	SLC	0.54	0.31	0.46	0.50

Table 4. C_{vg}valuesin $HH \cdot VV^*$ images.

Areas		Turbo Lee	Turbo SCC	Lee	SSC
Algiers	intensity	2.01	1.30	1.09	1.24
	SLC	0.75	1.89	1.05	1.52
Munich	intensity	0.21	0.99	0.48	0.65
	SLC	0.56	1.88	1.46	0.76

From tables 3 and 4, we note that the best global result in terms of edge preservation in the two cases intensity and complex filtering is given by the Turbo filter. We also note that the statistical results join well the conclusions of the visual evaluation.

8. CONCLUSION

The new formulation of the speckle noise model allows to study the noise characteristics of the off-diagonal PolSAR covariance matrix terms andalsoto knowbetterthe used data for the treatmentin order to achieveabetterresult.

According to the resultsobtained in theevaluation, we concludedthat the Turbo filterprovidesclear imageswith amuch reduced speckleand presents a goodcompromise betweensmoothing homogeneous areasand preserving edges.And that thanksto the principleof thismethod which consistsin joining together the advantages of the two filters: the refined Leefilterandwaveletfiltering. Thus, images are sharper, which makes it possible toproperly interpretthe dataand extractinformation. The filtered images will be used in various applications such as classification. However, theselection and adjustmentofparametersis not obvious, we had to do severalteststo obtaina good compromise betweensmoothinghomogeneous areasand preserving edges.

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