VARIABLE LOCAL WEIGHT FILTERING FOR POLSAR DATA SPECKLE NOISE REDUCTION

Alberto Alonso-González, Carlos López-Martínez, Philippe Salembier

Universistat Politècnica de Catalunya (UPC), Signal Theory and Communications Dept. (TSC)
Jordi Girona 1-3, 08034 Barcelona, Tlf. +34 934016785 Email: alberto.alonso@tsc.upc.edu

ABSTRACT

This paper presents a Polarimetric SAR data speckle filtering technique, based on a combined filtering in the spatial and polarimetric domains. It is based on a bilateral filtering employing distance measures over these domains. These measures concentrate all the information related to the domain structure that is needed for an adaptation to the scene morphology. A weighted average is performed over a given window favoring closer and similar pixels. As a consequence, an adaptive filtering is achieved, attaining higher filtering over homogeneous areas whereas point scatters remain almost unchanged. Results will be shown over a real RADARSAT-2 data.

***Index Terms*—** Synthetic Aperture Radar (SAR), SAR Polarimetry (PolSAR), Speckle Filtering, Bilateral Filter

1. INTRODUCTION

Polarimetric Synthetic Aperture Radar (PolSAR) is a type of multidimensional SAR system that exploits the vectorial nature of the electromagnetic waves to obtain diversity. Different combinations of the transmitted and received echo polarization are employed to obtain a better characterization of the target. It has demonstrated its usefulness to extract geophysical and biophysical information from the Earth surface.

However, the exploitation of PolSAR data has to cope with the added difficulty of the speckle noise. Although the speckle is a true electromagnetic measure, it has to be considered as a noise since it can not be predicted due to its complexity, and it has to be characterized statistically. Traditionally, under the complex Gaussian PolSAR data model, the estimated covariance matrix $\mathbf{Z}$ is employed

$$\mathbf{Z} = \langle \mathbf{k}\mathbf{k}^H \rangle_n = \frac{1}{n} \sum_{i=1}^{n} \mathbf{k}_i \mathbf{k}_i^H \tag{1}$$

where $\mathbf{k}_i$ represents the scattering vector of the i-th pixel among all the acquisitions, n represents the number of pixels and ^{H} represents the complex hermitian transpose.

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The main challenge when applying a statistical estimator is that it has to be employed over an homogeneous area of the data, but real PolSAR data is strongly inhomogeneous as it reflects the complexity of the scene. Consequently, some state-of-the-art speckle filtering techniques try to adapt to the image structure in order to avoid mixing heterogeneous regions of the data [1][2][3]. In this paper, a new approach following the same direction is proposed, based on the bilateral filtering [4][5], which performs a weighted average instead of (1) in order to adapt to the image structure. This adaptation is performed by adjusting the weights extending the idea of locality to both, the spatial and the polarimetric domains.

2. BILATERAL FILTERING

As mentioned before, the estimation of $\mathbf{Z}$ presented in (1) only makes sense over homogeneous areas of the data. The multilook filter, as the simplest approach, assumes spatial locality and defines a rectangular window around each pixel assuming that all the samples within the window are homogeneous. As a result, the obtained $\mathbf{Z}$ values over homogeneous areas will be correctly estimated employing n samples, defined by the window size, but the results will not be valid over contours or near point scatters, where inhomogeneous samples may be present within the fixed window. This effect may also be seen as a resolution loss, since, in fact, the multilook is a low-pass filter.

Bilateral filtering [4] incorporates the domain locality in addition to the spatial locality. For PolSAR data, it can be considered that homogeneous pixels will not only be located closely in space but also that they will have similar polarimetric values. In other words, it is also considering the polarimetric locality. Then, the idea is to average preferably samples close in both, the spatial and the polarimetric domains. Accordingly, a weighted average is performed, adjusting the weights depending on the closeness on both domains. The filtered covariance matrix $\mathbf{Z}^{ij}$ at position (i, j) can be expressed as

$$\mathbf{Z}^{ij} = k^{-1}(i,j) \sum_m \sum_n \tilde{\mathbf{Z}}^{mn} w_s(i,j,m,n) w_p\left(\tilde{\mathbf{Z}}^{mn}, \tilde{\mathbf{Z}}^{ij}\right) \tag{2}$$

where $m, n \in V(i,j)$ and $V(i,j)$ represents the local window around the pixel located at (i, j), $\tilde{\mathbf{Z}}^{ij}$ represents the input covariance matrix of that pixel, w_s is a weighting function depending on the spatial domain, w_p is a weighting function depending on the polarimetric domain and k is the normalization factor to preserve the radiometric power information

$$k(i,j) = \sum_m \sum_n w_s(i,j,m,n) w_p\left(\tilde{\mathbf{Z}}^{mn}, \tilde{\mathbf{Z}}^{ij}\right). \quad (3)$$

In order to exploit the spatial and polarimetric locality, as proposed before, w_s and w_p should be defined having the following properties:

1. w_s and w_p are within the interval $[0, 1]$, being higher for closer values in the spatial and polarimetric domains, respectively.
2. Then, it is assumed that $w_s(i, j, i, j) = 1, \ \forall\ i, j$ and $w_p(\mathbf{Z}, \mathbf{Z}) = 1, \ \forall\ \mathbf{Z}$.
3. To ensure that no global bias is introduced, w_s and w_p should be symmetric, that is, $w_s(i, j, m, n) = w_s(m, n, i, j)$ and $w_p\left(\tilde{\mathbf{Z}}^{mn}, \tilde{\mathbf{Z}}^{ij}\right) = w_p\left(\tilde{\mathbf{Z}}^{ij}, \tilde{\mathbf{Z}}^{mn}\right)$ for all possible values of i, j, m, n.

In this work, we propose the formulation of w_s and w_p based on two different distances for the spatial and the polarimetric domains

$$w_s(i,j,m,n) = \frac{1}{1 + \frac{d_s^2(i,j,m,n)}{\sigma_s^2}} \quad (4)$$

$$w_p\left(\tilde{\mathbf{Z}}^{mn}, \tilde{\mathbf{Z}}^{ij}\right) = \frac{1}{1 + \frac{d_p^2\left(\tilde{\mathbf{Z}}^{mn}, \tilde{\mathbf{Z}}^{ij}\right)}{\sigma_p^2}} \quad (5)$$

where σ_s and σ_p represent the weights sensitivity, and d_s and d_p are the distances in the spatial and polarimetric domains, respectively

$$d_s^2(i,j,m,n) = (i-m)^2 + (j-n)^2 \quad (6)$$

$$d_p^2\left(\tilde{\mathbf{Z}}^{mn}, \tilde{\mathbf{Z}}^{ij}\right) = \left(\sum_{k=1}^{p}\left(\frac{(\tilde{Z}_{kk}^{mn})^2 + (\tilde{Z}_{kk}^{ij})^2}{\tilde{Z}_{kk}^{mn}\tilde{Z}_{kk}^{ij}}\right) - 2p\right) \quad (7)$$

where Z_{ij} is the index notation for the (i, j)th element of the p by p matrix $\mathbf{Z}$.

Note that d_s^2 is the squared Euclidean distance and d_p^2 defined in (7) is based on the diagonal revised Wishart measure defined in [3]. Some additional measures are defined and analyzed in [3], but we will consider only diagonal measures, since the estimated covariance matrix $\tilde{\mathbf{Z}} = \mathbf{k}\mathbf{k}^H$ for the original pixels is singular, having rank equal to one.

As opposite to the classical multilook filtering, having a constant number of averaged pixels, the bilateral filtering will have, in general, a different number of averaged samples for each pixel. However, this information may be directly extracted from the $k(i, j)$ parameter (3), which is available for the interpretation of the results.

3. ITERATIVE REFINEMENT APPROACH

When applying the bilateral filter defined in Section 2 over PolSAR data, all the samples within the local window $V(i, j)$ will be weighted according to their proximity in the spatial and polarimetric domains with the central pixel. However, since SAR data is highly affected by speckle, the noise of this central pixel value will have a great impact on the calculated w_p weights, resulting also in a noisy filtered image. To mitigate this effect, an iterative approach is proposed, employing the result of one iteration to calculate the weights in the next iteration, which is represented on Fig. 1.

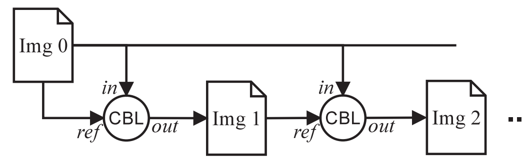


Fig. 1: Iterative refinement approach diagram.

CBL stands for *cross-bilateral filter* [6], which corresponds to the bilateral filter defined in (2) when the weighted averaging is performed over the input image *in* while the weights are calculated over the reference image *ref*

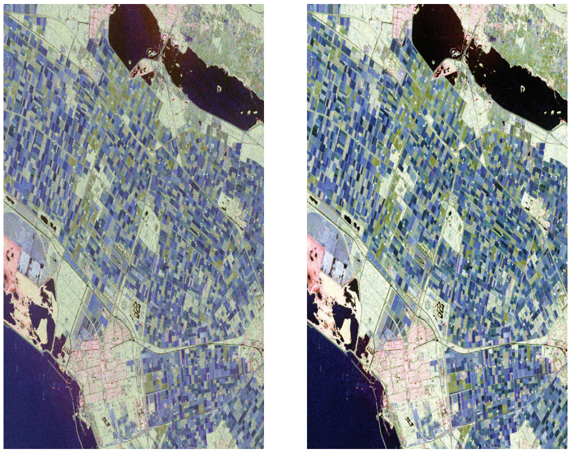
$$\mathbf{Z}_{\text{out}}^{ij} = k^{-1}(i,j)\sum_m \sum_n \tilde{\mathbf{Z}}_{\text{in}}^{mn} w_s(i,j,m,n) w_p\left(\tilde{\mathbf{Z}}_{\text{ref}}^{mn}, \tilde{\mathbf{Z}}_{\text{ref}}^{ij}\right). \quad (8)$$

Note that the scheme presented in Fig. 1 is not an iterative filtering, since at each iteration the original image *Img 0* is filtered. Instead, it is an iterative weight refinement scheme. Iterative filtering will have the disadvantages of propagating errors and resulting in an almost unusable k parameter, encumbering further data analysis and interpretation.

4. RESULTS

In this work, the proposed bilateral filtering scheme has been employed to process a RADARSAT-2 Fine Quad-Pol image corresponding to a test-site in Flevoland, the Netherlands. The data was acquired on April 4th, 2009, with the beam FQ13, during the ESA AgriSAR 2009 campaign, and is presented in Pauli RGB composition in Fig. 2a. The scene is composed mainly by an area of agricultural fields and some sea surface and urban areas. Fig. 2b presents the filtered image employing the proposed bilateral filter with $\sigma_s = 3$ and $\sigma_p = 0.6$, employing a 11x11 pixel local window V and with 5 iterations of the proposed weight refinement scheme.

Fig. 3 shows a comparison of the filtered image Fig. 2b with the 7x7 multilook filtering. The resolution loss implied by the multilook filtering over the contours may be clearly seen when comparing Figs. 3a and 3b. The proposed bilateral filtering scheme has a better spatial resolution preservation since it does not merge inhomogeneous samples over contours. This effect may be inferred from Fig. 3c, where the k parameter obtained by the filter is shown. The number of filtered pixels over homogeneous areas is close to 40 pixels,



(a) Original (b) CBLF, 5it, $\sigma_s = 3, \sigma_p = 0.6$

Fig. 2: Original (a) and filtered (b) Pauli RGB images.

as it may be seen over the fields on the top of the image or the sea at the bottom part. However, over the contours, since the close pixels are far away in the polarimetric domain, d_p increases and w_p decreases resulting in a lower number of filtered pixels k. The same effect may be seen for point targets and small details over urban area. Note that, as a comparison, the equivalent k parameter for the multilook filtering is constant $7 \cdot 7 = 49$ pixels for every pixel.

Fig. 4 shows the Entropy (H) and averaged alpha angle ($\bar{\alpha}$), obtained from the eigen-analysis of the estimated covariance matrix **Z**, for the filtered images employing the 7x7 multilook and the proposed method in Figs. 3a and 3b, respectively. As it may be seen, qualitatively the same values are obtained over homogeneous areas, whereas the small details of the urban area are enlarged by the multilook filtering according to its window whereas they are kept small with the bilateral filtering, since it avoids the mixture of non-homogeneous samples, having also a better preservation of the spatial resolution.

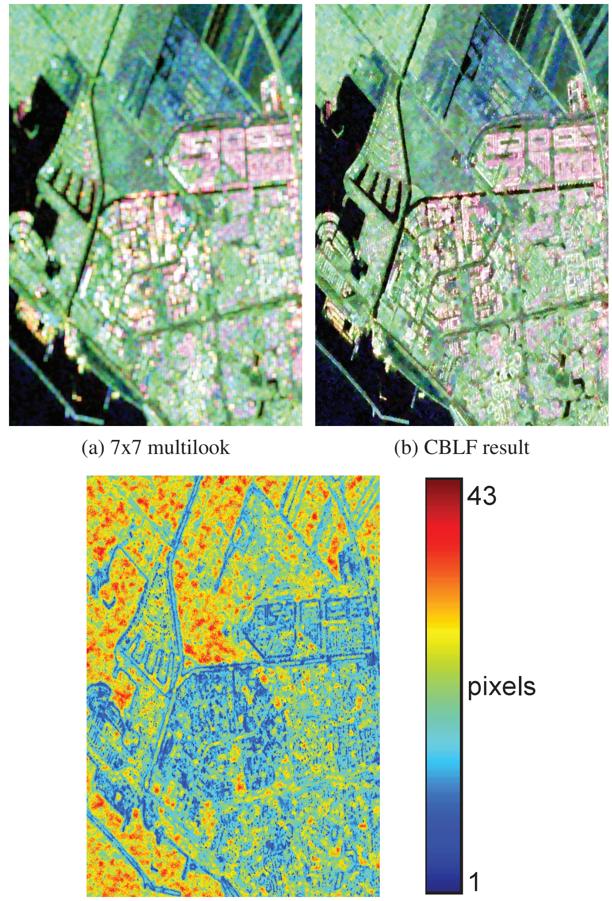
On Fig. 5 the 50-bin histograms of the k parameter are shown for different values of σ_s and σ_p. 5 iterations have been considered on the scheme presented in Fig. 1 on all cases. The first row presents the effect of changing the σ_s parameter over the histograms, whereas on the second row σ_s is fixed and different values of σ_p are employed. Increasing σ_s implies a higher number of samples filtered per pixel, as shown on Figs. 5a to 5c. On the other hand, changing σ_p, on Figs. 5d to 5f, also affects the k parameter in the same way, but in this case the shape of the histograms is substantially changed. Additionally, this parameter has an important impact on the contours preservation, since a too large value may imply a mixture of inhomogeneous samples, while a too small value will imply a low filtered result. Nonetheless, note that the proposed filtering tends to the multilook filter over the window V when $\sigma_s \to \infty$ and $\sigma_p \to \infty$.

To make a quantitative evaluation of the filtering technique, simulated data is generated and processed, as described in [7]. A 512x512 pixel crop is selected from the image, shown on Fig. 6a, and it is segmented with the technique presented in [3], exposed on Fig. 6b, conforming the ground truth for the simulation process. From this synthetic ground truth 25 different realizations are generated as, for instance, the one presented on Fig. 6c. This simulated data is filtered with the proposed method, Fig. 6d, and the result is compared with the synthetic ground truth pixel by pixel employing the measure

$$E_R(X, Y) = \frac{1}{n_h n_w} \sum_{i=1}^{n_h} \sum_{j=1}^{n_w} \frac{\|\mathbf{Z}_X^{ij} - \mathbf{Z}_Y^{ij}\|_F}{\|\mathbf{Z}_Y^{ij}\|_F} \quad (9)$$

where n_h and n_w are the image height and width in pixels and $\mathbf{Z}_X^{ij}$ represents the (i, j)th pixel value of image X.

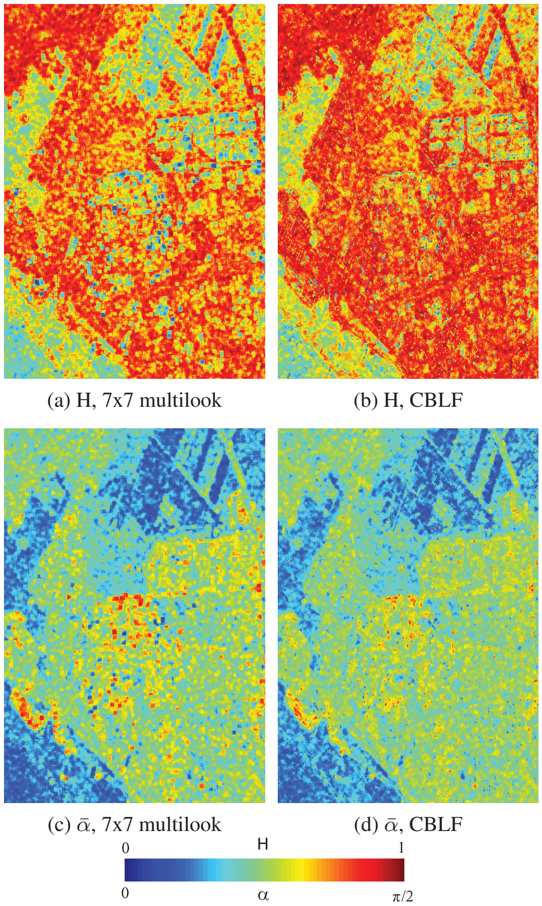
Fig. 6e presents the measure (9) for the proposed technique employing different values of σ_s and σ_p. It may be seen that there is a minimum for every combination of parameters. However, note that E_R is the average error for all the image pixels and then the filtering over homogeneous areas is more significant than over contours since they cover a larger amount of pixels. Hence, the optimum values shown on Fig. 6e may not be the best in terms of contours preservation.



(a) 7x7 multilook (b) CBLF result

(c) CBLF k parameter

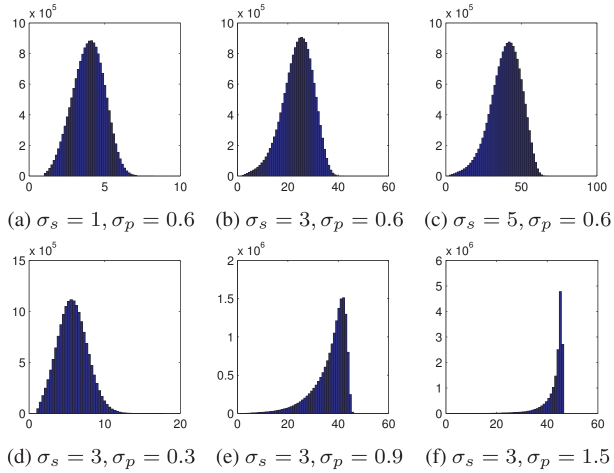
Fig. 3: 7x7 multilook (a), filtered (b), and number of pixels averaged, the k parameter (c), detail images from Fig. 2.



(a) H, 7x7 multilook (b) H, CBLF

(c) $\bar{\alpha}$, 7x7 multilook (d) $\bar{\alpha}$, CBLF

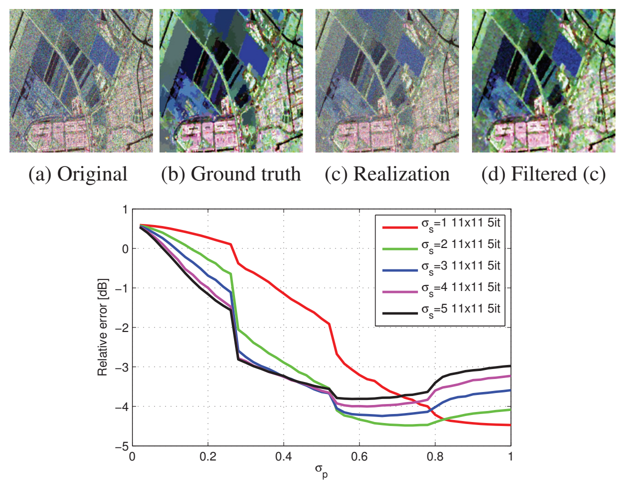
Fig. 4: Entropy (H) and averaged alpha angle ($\bar{\alpha}$) for 7x7 multilook and the proposed bilateral filtering method.



(a) $\sigma_s = 1, \sigma_p = 0.6$ (b) $\sigma_s = 3, \sigma_p = 0.6$ (c) $\sigma_s = 5, \sigma_p = 0.6$

(d) $\sigma_s = 3, \sigma_p = 0.3$ (e) $\sigma_s = 3, \sigma_p = 0.9$ (f) $\sigma_s = 3, \sigma_p = 1.5$

Fig. 5: Histograms of k for different σ_s and σ_p with 5 weight refinement iterations and 11x11 local window V.



(a) Original (b) Ground truth (c) Realization (d) Filtered (c)

(e) Relative error for different σ_s and σ_p

Fig. 6: Simulated data evaluation from a real image.

5. CONCLUSIONS

In this paper a new PolSAR speckle filtering technique is introduced, based on the bilateral filtering. This technique is able to achieve good filtering, comparable to the classical multilook filtering, while also being able to preserve contours and small details. A weighted average is performed favoring similar pixels in the spatial and polarimetric domains. To evaluate the closeness in these domains a distance based metric is employed, which concentrates the domain structure knowledge. As a result, a different number of samples is averaged for every pixel of the image. However, this value may be extracted from the k parameter of the filter, being available for further interpretation or information extraction.

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