Dual-Channel PolSAR Speckle Reduction Using Non-Local Means Filter

Jingliang, Hu, German Aerospace Center (DLR-IMF), Jingliang.hu@dlr.de, Germany
Andreas, Schmitt, German Aerospace Center (DLR-DFD), Andreas.Schmitt@dlr.de, Germany
Xiaoxiang, Zhu, German Aerospace Center (DLR-IMF) & Technical University of Munich (TUM-SIPEO), xiao.zhu@dlr.de, Germany

Abstract

Intelligent speckle filters promote the efficient usage of PolSAR data. It has been validated that non-local means filter is capable of reducing noise while preserving details. This paper applies a non-local filtering scheme for dual-channel TerraSAR-X PolSAR data. One of the key points in Non-local means filter is the similarity measurement. In this study, detection similarity and Log-Euclidean similarity are used and compared regarding dual-channel PolSAR. The analysis showed that each similarity approach leans to one side of the speckle reduction-detail preservation trade-off.

1 Introduction

Dual-channel polarized synthetic aperture radar (dual-pol SAR) data owns its unique advantages. It provides more polarized information comparing to single-channel data. Its performance is also competitive to quad-channel PolSAR data on some applications, while it has wider swaths and higher geometric resolution with current sensors [1].

Non-local means filter [2] searches similar pixels in the whole image and conducts weighted mean filtering. This procedure utilizes the redundancy of image and breaks the local neighborhood limitation. When the filter searches for similar pixels, local patches are compared which ensures the detail preservation property of Non-local means filter.

The key points of applying non-local means filter on dual-pol SAR data are the similarity measurement and weight kernel definition. This paper focusses on comparing two different similarity approaches of non-local means filter regarding dual-pol SAR data. The filtered results and empirical probability of similarity values are used to find out which side of the trade-off (speckle reduction and detail preservation) the similarity approaches incline to.

2 PolSAR data

In this work, the two co-polarized channels are used, namely horizontal emitted and horizontal received signal (S_{HH}) and vertical emitted and vertical received signal (S_{VV}). The scattering vector is represented as (1).

$$\mathbf{S} = \begin{bmatrix} S_{\mathrm{HH}} \\ S_{\mathrm{VV}} \end{bmatrix} \tag{1}$$

H: Horizontal linear polarization
V: Vertical linear polarization

Then, the covariance matrix of dual-pol SAR data can be defined as $\mathbf{C} = \langle \mathbf{SS}^* \rangle$, where $*$ is the conjugate transpose, and $\langle \cdot \rangle$ is the expectation.

3 Non-local means filter

3.1 Similarity approaches

A test for equality of two complex Wishart matrices is developed and further derived into a similarity measurement of two PolSAR covariance matrices [3], which is named as **detection similarity (DS)**.

$$\Delta(\mathbf{C}_1, \mathbf{C}_2) = -\log\left(\frac{|\mathbf{C}_1|^L |\mathbf{C}_2|^L}{\left|\frac{1}{2}\left(\mathbf{C}_1 + \mathbf{C}_2\right)\right|^{2L}} \right) \tag{2}$$

where $\mathbf{C}_i$ = PolSAR covariance matrix
i = indicate different pixel
L= number of looks
|.| = determinate of matrix
Δ= similarity value of two pixels

Alternatively, the **Log-Euclidean** (**LE**) distance in [4] could be applied on PolSAR data to work as a similarity measurement.

$$\Delta(\mathbf{C}_1, \mathbf{C}_2) = \left\| \log(\mathbf{C}_1) - \log(\mathbf{C}_2) \right\| \tag{3}$$

where $\log()$ = matrix logarithm
$\|\cdot\|$ = Euclidean norm

The original study [4] only applied the diagonal elements of the Hermitian matrix, which is sufficient for their applications. Our recent work applied this metric on PolSAR data acting as similarity measures between pixels. Furthermore, the off-diagonal elements are also included in our work for the reason that these elements include the coherence and phase difference information of two Polarimetric channels.

Depend on the definitions of similarity measurements, when two pixels are identical, similarity value equals 0, otherwise the values increase.

3.2 Weight kernel

Our previous work [5] on fully polarized data introduced a strategy of deciding similarity boundary to differ pixels based on homogeneous and heterogeneous areas.

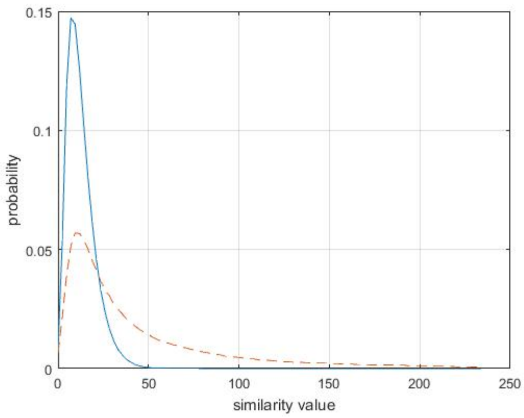


Figure 1: Empirical probability distribution of similarity value; Blue solid curve: similarity values calculated from homogeneous area; Red dotted curve: similarity values calculated from heterogeneous area

The heterogeneous area here means that it is an area including different ground targets. When calculating the similarity value, there of course exist comparisons between the same targets. However, there also exist comparisons between different targets. Furthermore, the different targets' comparison is the exact reason why the right tail of the red dotted curve exists. In other words, the blue solid curve is the empirical probability distribution of similarity values measured from homogeneous pixels. The red curve is the combination of the probability of the blue one and the empirical probability distribution of similarity values measured from different pixels.

Afterwards, the similarity value corresponding to the intersection point is chosen as the similarity boundary. The decision of the similarity boundary is a result of estimation detection problem based on empirical probability.

Our recent work utilizes this similarity boundary to construct a data driven weight kernel. Firstly, it is calculated that the empirical cumulative probability $\mathrm{ecpf}(\Delta)\ \Delta \in [0 \quad boundary]$ of similarity values, which are calculated from homogeneous area and range from 0 to the chosen boundary. Then, the weight kernel is defined as

$$w(\Delta) = \begin{cases} 1-\mathrm{ecpf}(\Delta) & \Delta\in[0 \quad boundary] \\ 0 & \Delta\in(boundary \quad +\infty] \end{cases} \tag{4}$$

where Δ = similarity value of two pixels
$w(\Delta)$ = weight values

4 Experiments and discussions

4.1 Dual-channel PolSAR Data

The experimental data in this paper is the dual-channel co-polarized high resolution spotlight TerraSAR-X data of Munich, Germany, which can be shown as the image **Figure 2** (b). The white rectangles delineate selected homogeneous areas. And the red ones show the boundaries of heterogeneous areas. The corresponding area is also shown in optical image in **Figure 2** (a).

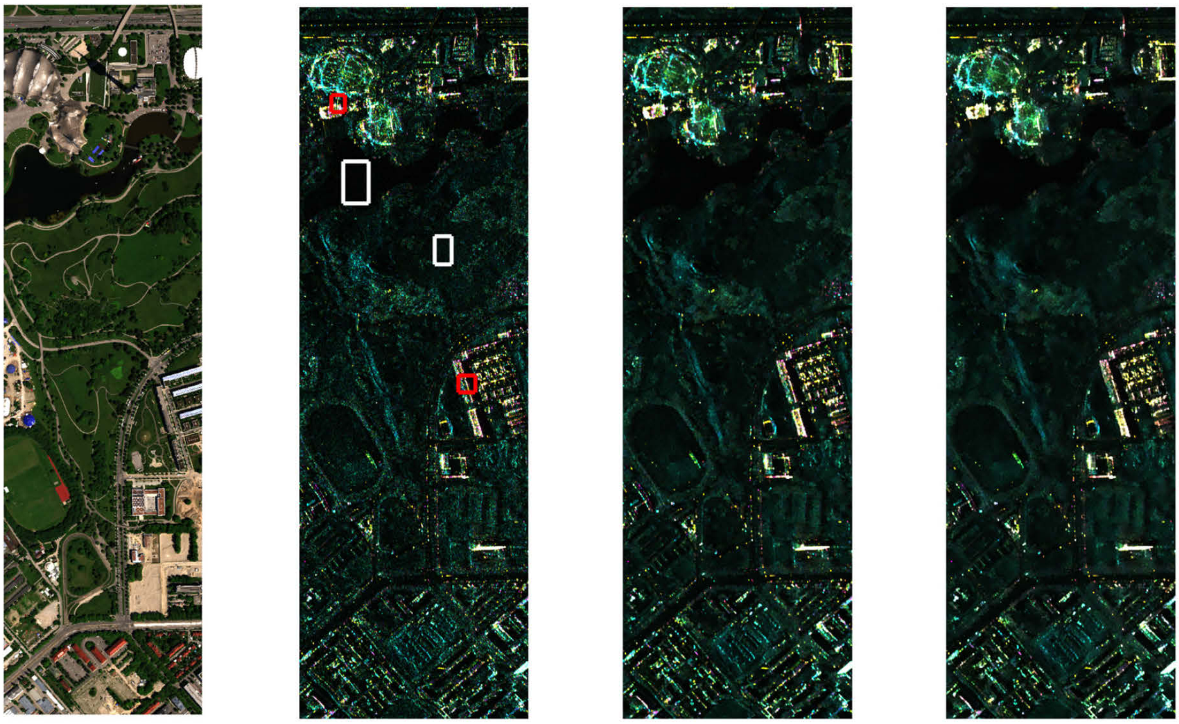
4.2 Evaluation

We applied the proposed algorithm on the dual-channel PolSAR data mentioned above. Two similarity approaches, namely the detection similarity approach and the Log-Euclidean approach, are used. It is worthy to mention that the searching window is 25 by 25 and patch size is 3 by 3 in the experiments.

The results are shown in **Figure 2** (c) and (d), respectively. In the following, the performances of the two similarity approaches are analyzed regarding speckle reduction and detail preservation of the filtered results and the empirical cumulative probability.

4.2.1 Speckle reduction

In order to evaluate the performance on speckle reduction, the equivalent number of looks (ENL) is calculated



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

Figure 2: Experimental data of Munich; (a) optical data; (b) TerraSAR-X dual-pol SAR data; (c) filtered data using detection similarity; (d) filtered data using Log-Euclidean- similarity.

as the indication regarding the co-diagonal elements of the selected homogeneous area. From **Figure 2,** one might not find any differences by visual inspection. However, in Table 1, the ENL indication tells that Log-Euclidean similarity has stronger effect on speckle reduction.

Area	Band	Original data	DS	LE
1	HH	1.8487	17.8695	25.7367
	VV	2.1352	26.2267	42.8697
2	HH	2.0833	23.2486	37.1897
	VV	2.2690	28.5745	64.9222

Table 1: ENL of the original and filtered dual-pol SAR data

4.2.2 Detail preservation

In this section, the edge preservation degree of ratio of average (EPD-ROA) introduced in [6] works as the indication to exam the detail preservation performance of speckle reduction algorithm.

$$\text{EPD-ROA}=\frac{\sum_{i=1}^{m}\left|I_{D1}(i)/I_{D2}(i)\right|}{\sum_{i=1}^{m}\left|I_{O1}(i)/I_{O2}(i)\right|} \qquad (5)$$

m =number of pixels in selected area
i =ith pixel in selected area
I_{D1}, I_{D2} =adjacent pixels' values of filtered data
I_{O1}, I_{O2} =adjacent pixels' values of averaged data

The ideal case of calculating EPD-ROA requires the data without noise or limited noise. In our study, the data is simply estimated by averaging using a 3 by 3 sliding window to avoid the influence of speckle. This easy efficient procedure reduces noise and preserves the details relatively. In this test, two structure areas are selected to examine the detail preservation performance.

Area	Band	DS	LE
1	HH	0.9460	0.8629
	VV	0.9819	0.7592
2	HH	0.8934	0.6608
	VV	0.9616	0.7646

Table 2: EPD-ROA value of two structure areas

According to definition of EPD-ROA(5), when the value is closer to 1, it means that the corresponding filter preserves better details. **Table 2** shows the indication for the filtered data. Detection similarity approach has a better performance on detail preservation.

4.2.3 Similarity analysis

In section 3.2, it is explained that the similarity boundary decision is a solution to the detection problem of estimation theory. When using different similarity approaches on the same areas to decide the boundary, it gives a probability indication as follows to analyze the performance of similarity approaches.

The probability $P(similarity < boundary \mid H)$ is the cumulative probability of similarity values smaller than the boundary, under the condition that similarity values are calculated from homogeneous area. It is the probability of correct hit in estimation detection problem.

Because the fact that, for the same selected areas, those similarity approaches measure the same physical phenomenon underneath, the probability of correct hit depends only on the approaches themselves.

Explicitly, the higher value of the cumulative probability means the similarity approach considers more pixels as similar pixels. Therefore, it has stronger effect on speckle reduction.

Two homogeneous areas (H1 and H2) and two heterogeneous (h1 and h2) areas are selected to conduct this experiment. And the probability is shown in **Table 3**.

	Combination of areas			
	H1h1	H1h2	H2h1	H2h2
DS	0.8435	0.8889	0.8405	0.8823
LE	0.8842	0.9323	0.8944	0.9379

Table 3: $P(similarity < boundary \mid H)$ empirical cumulative probability of similarity smaller than the boundary regarding homogeneous pixels

From table 3, it shows that Log-Euclidean similarity approach has higher probabilities of the correct hit for all experiments, which indicates that Log-Euclidean has better performance on speckle reduction.

5 Conclusions

In this paper, we updated the Log-Euclidean similarity approach by including the off-diagonal elements of the dual-pol SAR covariance matrix. The non-local means filter is used on the dual-pol TerraSAR-X data. After the filtering procedure, not only the speckle reduction and detail preservation of filtered data are used to evaluate the similarity approaches, but also the empirical cumulative probability is used in this paper. Based on the concrete content lies in the data, the empirical cumulative probability combined with the similarity boundary decision strategy provides a data-driven indication to the evaluation of similarity approach.

Most importantly, we analyzed and compared the detection similarity approach and the Log-Euclidean similarity approach based on their usage on the experimental data. It is shown from the final filtered results and the analysis of similarity that, with respect to the experimental data, the Log-Euclidean similarity approach has a stronger effect on speckle reduction and detection similarity approach has a stronger effect on detail preservation. Therefore, the selection of these two similarity approaches bases on the user's preference and purpose of application.

Acknowledgment

This work is supported by the Helmholtz Association under the framework of the Young Investigators Group "SiPEO" (VH-NG-1018, www.sipeo.bgu.tum.de). TerraSAR-X data were obtained through TerraSAR-X science project LAN 2067 (Principal Investigator: Xiaoxiang Zhu). We also want to thank Dr. Charles Deledalle for the inspiring suggestions.

References

[1] Leichtle T, Schmitt A, Roth A, et al.: On the capability of different SAR polarization combinations for agricultural monitoring, IGARSS, 2012.

[2] Buades A, Coll B, Morel J M.: A non-local algorithm for image denoising, CVPR, 2005.

[3] Chen J., Chen Y., An, W., Cui, Y., and Yang, J.: Nonlocal filtering for polarimetric sar data: A pretest approach, IEEE Transactions on Geoscience and Remote Sensing., 2011

[4] Arsigny V, Fillard P, Pennec X, et al.: Log-Euclidean metrics for fast and simple calculus on diffusion tensors, Magnetic resonance in medicine, 2006.

[5] Hu J, Guo R, Zhu X, et al.: Non-Local Means Filter for Polarimetric SAR Speckle Reduction-Experiments Using Terrasar-X Data, PIA, 2015.

[6] Feng, H., Hou, B., and Gong, M.: Sar image despeckling based on local homogeneous-region segmentation by using pixel-relativity measurement, IEEE Transactions on Geoscience and Remote Sensing, 2011.