

MIXTURE DESCRIPTION OF POLARIMETRIC SAR IMAGES AND IMPROVED NON-LOCAL SPECKLE FILTERING

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ABSTRACT

We introduce a polarimetric SAR speckle filter by combining finite mixture distributions and the so-called non-local filtering scheme. The finite mixture distributions are used to describe the statistical properties of the highly textured, heterogeneous scene in high-resolution SAR images. The non-local filtering scheme is used to test similarity in the local patterns to include sufficient pixels for better speckle reduction. The filter is capable of retaining distinctive scattering mechanisms from the onset. The improvement is demonstrated using DLR's high-resolution F-SAR images.

Index Terms— polarimetric SAR speckle, non-local filter, mixture distribution.

1. INTRODUCTION

Synthetic Aperture Radar (SAR) images are inherently contaminated by the interference of multiple coherent echoes, which results in the granular noise-like feature known as speckle. Speckle makes the interpretation and analysis of SAR images very difficult. Therefore, SAR images are first filtered before any additional analyses are performed. Polarimetric SAR (PolSAR) takes observations from multiple channels. In this case, speckle perturbs not only each individual channel but also the important inter-channel correlations. A polarimetric speckle filter should treat all the channels together as a single entity to preserve the scattering mechanisms of the targets [1]. The statistical properties of polarimetric speckle are contained in the covariance matrix which follows a Wishart distribution.

A speckle filter needs to balance two competing needs on speckle reduction and small-feature preservation. A critical step is to identify the pixels that are “similar” such that more pixels can be included by expanding the local neighborhood [2,3]. Over an arbitrarily large neighborhood, the so-called non-local (NL) scheme was proposed in [3] assuming Gaussian additive noise where Euclidean distance was assessed as a similarity measure to match local patterns. This model is obviously inappropriate for SAR speckle. In [4] a NL filter based on Wishart distributions was

introduced for PolSAR speckle filtering. However, working with covariance matrices necessitates multi-looking operation. Although in theory the multi-looking can be circumvented by using diagonal covariance matrices, all the cross-channel correlations will be discarded and the discrimination power is fairly low over single-look pixels.

At high-resolution, speckle can be highly textured and multi-looking will mix different scattering mechanisms. The highly textured speckle can be described using a finite mixture model. Then the covariance matrices representing the speckle characteristics will be determined globally. In this paper we investigate the NL filtering coupled with mixture description. The goal is to preserve distinct scattering mechanisms to the greatest extent for high-resolution PolSAR speckle filtering.

2. REVIEW

2.1. Mixture Speckle Model

Common PolSAR speckle model follows complex normal distribution in single-look data or complex Wishart distribution in multi-looked data. This is not always true in high-resolution images due to texture contribution. Textured speckle can be better evaluated with the multiplicative SIRV model [5], where a scalar texture variable scales the whole polarimetric speckle. However, application of the SIRV model will be challenging when resolution is very high, because (1) the better resolved scattering mechanisms prevent using stationary covariance matrices and (2) the diverse texture details require different distributions.

Instead, a finite mixture model can be used to adaptively fit the textured speckle. Assuming the single-look polarimetric vector \mathbf{x} follows a zero-mean circular normal distribution, the density function can be written as

$$f(\mathbf{X}) = \frac{1}{\pi^3 |\mathbf{C}|} \exp\{-tr(\mathbf{C}^{-1}\mathbf{X})\} \quad (1)$$

where $\mathbf{X} = \mathbf{x}\mathbf{x}^H$ and \mathbf{C} is the covariance matrix. A finite mixture model is constructed of multiple normal distributed components as

$$f(\mathbf{X}) = \sum_{k=1}^K \pi_k f_k(\mathbf{X}|\mathbf{C}_k) \quad (2)$$

where component k features a covariance matrix \mathbf{C}_k and π_k represents its mixing weight among K components. Both

π_k and \mathbf{C}_k can be iteratively estimated using an expectation-maximization (EM) algorithm.

With a reasonable large K , the mixture model is capable of accurately expressing the observed speckle distribution for all the targets even within a large neighborhood. The set of fitted model parameters $\{\mathbf{C}_k\}$ contains all distinctive scattering mechanisms.

2.2. Non-local Filtering

The NL filtering is built on a weighted averaging scheme that selects and includes as many pixels as possible. Over noisy measurements, pixels are deemed as similar if their surrounding patches share the same local pattern that is evaluated through a distance measure. The filtered pixel is computed from

$$\mathbf{X}_f(p) = \frac{1}{W(p)} \int_{\Omega} \exp\left\{-\left(\frac{D_{pq}}{D_h}\right)\right\} \mathbf{X}_f(q) dq \quad (3)$$

where p and q indicate pixel locations, D_{pq} is the distance between the pixels at p and q , D_h defines the filtering strength, and W defines the normalization term. The filter acts on all pixels within an arbitrary searching domain Ω .

The distance D_{pq} is assessed over the local patches centered at p and q . It collects the inter-pixel distance within the local patches such that $D_{pq} = \sum d_{ij}$, $i = p \cdot, j = q \cdot$. For Gaussian additive noise [3],

$$d_{ij} = \|\mathbf{x}_i - \mathbf{x}_j\|^2 \quad (4)$$

For multi-looked polarimetric speckle \mathbf{X} [4],

$$d_{ij} = (n_i + n_j) \ln \left| \frac{n_i \mathbf{x}_i + n_j \mathbf{x}_j}{n_i + n_j} \right| - n_i \ln |\mathbf{x}_i| - n_j \ln |\mathbf{x}_j| \quad (5)$$

where n represents the associated number of looks. Eq.(5) is derived from the generalized likelihood ratio based on Wishart distribution. The number of looks shall be greater than 3 for PolSAR speckle to ensure non-zero determinants.

3. MIXTURE BASED NON-LOCAL FILTERING

The essence of NL filtering is taking the contribution of many pixels to reduce speckle. Through an appropriate distance measure, those non-neighboring pixels can be included without blurring deterioration. In this sense, the mixture fitting offers an ideal NL implementation. Note that the maximum a posterior estimator (MAP) of the covariance matrix for \mathbf{X} can be derived as,

$$\hat{\mathbf{C}}(\mathbf{X}) = \arg\max_{\mathbf{C}_k} \pi_k f_k(\mathbf{X}|\mathbf{C}_k) \quad (6)$$

Replacing the observations with the fitted set $\{\mathbf{C}_k\}$ forms a MAP based “non-local” assignment, since the parameters are globally determined.

However, it alone does not render much filtering because the assignment would be predominately based on the noisy data, which has a very limited power of discrimination. Fig.1 shows an example scene of DLR’s high-resolution F-SAR images. Fig.2 shows the direct assignment after fitting the data with a 30-component mixture model. Although the image is reduced to a small

number of texture components, it does not embody a filtered appearance.

On the other hand, the Wishart-based NL filter would require prior multi-looking for valid covariance matrices unless the covariance matrices are diagonal. Discarding polarimetric correlations will make the single-look imagery admissible. However, the noisy data again has limited power of discrimination. For example, the distance for the diagonalized PolSAR speckle can be derived from the generalized likelihood ratio as

$$d = \sum_{m=1}^3 2 \ln \left(\frac{|x_m|^2 + |y_m|^2}{2} \right) - \ln |x_m|^2 - \ln |y_m|^2 \quad (7)$$

where x_m and y_m are the element of polarimetric vector \mathbf{x} . Assuming a 10% false discrimination rate, the NL filtered image is shown in Fig.3. It is hard to find a strength parameter to adequately balance smoothing and blurring.

3.1 Filtering Single-look Images

It is of some merit to incorporate the mixture fitting with the NL filtering scheme. Running a mixture fitting to single-look PolSAR imagery (1) allows adaptive characterization of the heterogeneous scene on the high-resolution images and (2) leads to globally estimated covariance matrices of the underlying components. The following NL scheme further extends filtering to a large window. The first step generates estimation of texture patterns and the second step assesses pattern similarity.

In this case, the estimated covariance matrices can be regarded as the expression of true scattering patterns since they are estimated from a large sample. The inter-pixel distance can be evaluated by Bartlett distance between \mathbf{C}_i and \mathbf{C}_j in the form of [6]

$$d_{ij} = 2 \ln \left(\left| \frac{\mathbf{C}_i + \mathbf{C}_j}{2} \right| \right) - \ln |\mathbf{C}_i| - \ln |\mathbf{C}_j| \quad (8)$$

which is a special case of (5) where both n_i and n_j equal to 1. The distance between \mathbf{C}_i and \mathbf{C}_j can also be evaluated through the Kullback-Leibler divergence, namely

$$d_{ij} = \text{tr}(\mathbf{C}_i^{-1} \mathbf{C}_j) + \text{tr}(\mathbf{C}_j^{-1} \mathbf{C}_i) - 6 \quad (9)$$

where the divergence has been symmetrized. Note that unlike (5), the distances in (8) and (9) are deterministic.

3.2 Filtering Strength Parameter

A NL filter is parameterized by the local patch size, the searching domain Ω , and the strength parameter D_h . Among them, D_h plays the most important role by weighting the pixels differently.

It is not necessary to set the searching domain too large for satisfactory filtering because the extra gain incurred will eventually be negligible after the filter finds a certain amount of similar pixels. Searching over a large Ω increases the computation time.

The local patch size and the strength parameter D_h together determine how aggressively the local patterns are matched. For a given local patch size, D_h can be statistically

yet empirically determined. When D_{pq} is large, the probability to see false discrimination is low and that pixel should be excluded from filtering. Thus D_h can be empirically associated with the false discrimination rate P_F . Lower D_h scales the weights to take larger D_{pq} in the filter and leads to stronger smoothing.

If n_i and n_j are large, the distance statistic (5) follows a chi-square distribution [7] and the corresponding false discrimination rate can be easily derived. For smaller n_i or n_j , a better approximation can be found in [8].

For the single-look case (8) and (9), we can derive P_F from the likelihood ratio test which is known to be most powerful according to the Neyman-Pearson lemma:

$$P_F = P_r\{tr[(\mathbf{C}_i^{-1} - \mathbf{C}_j^{-1})\mathbf{X}] < \ln|\mathbf{C}_j| - \ln|\mathbf{C}_i|\}_{\mathbf{C}_i^{-1}} + P_r\{tr[(\mathbf{C}_j^{-1} - \mathbf{C}_i^{-1})\mathbf{X}] < \ln|\mathbf{C}_i| - \ln|\mathbf{C}_j|\}_{\mathbf{C}_j^{-1}} \quad (10)$$

It is not convenient to develop a closed-form solution but the probability can be easily solved numerically. From data we found the distance measures in (8) and (9) are closely related and P_F shows clear dependency on either of them. Thus the parameter D_h can be approximately determined from the numerical solution of (10). With the statistically derived D_h , the difference between the two distance measures is insignificant in the filter and we opted with the Bartlett distance.

3.3 Number of the Mixture Components

The mixture fitting through EM algorithm requires an initial set of covariance matrices and a known number of the mixture components. The EM algorithm is destined to converge but different initializations result in different convergence points, whereas the number of components controls how good a speckle description can be attained.

The initialization is not critical in this application. The goal during the fitting step is to find a valid, global-wise speckle description, judged by increased likelihood. The likelihood gain with mixture fitting outpaces the perturbation associated with initialization. Moreover, we do not use the fitted model to make a hard assignment.

However, the number of components needs to be carefully selected. If it is too small, the fitted model gives an insufficient speckle description and some meaningful variations will be lost during filtering. If it is too large, the fitted model overfits the speckle with poor discrimination power and the filter will suffer the same problem balancing smoothing and blurring. An exact choice can be possibly made by minimizing the Bayesian Information Criterion (BIC) [9] among varying numbers of components. In practice this method is unacceptable due to the tremendous computation cost. Fortunately, there is a wide margin for imperfect selections. We found a good compromise in fitting with \sqrt{N} components for an $N \times N$ image.

3.4 Comparison

Table 1: Filter strength parameters for different distance measures at $P_F=0.1$

Non-local Filter Type	Filter Strength Parameter
Wishart based	80
Diagonal-covariance based	22
Mixture based	24

For all the NL filters, we set the local patch size to 3×3 and the searching domain size to 15×15 . A pre-filtering with 3×3 boxcar was used to estimate covariance matrices for the Wishart-based NL filter. The image size shown in Fig.1 is 950×750 and we used 30 normal components in the mixture fitting. We adopted the same P_F for the filtering strength parameter, following $D_h \approx D_{pq}(P_F = 0.1)$. The calculated values are listed in Table 1 for reference.

Overall, all the NL filters preserve the edges and the boundaries very well. The diagonal-covariance based NL filter leaves isolated residue speckle on the image (Fig.3), whereas both the Wishart-based NL filter (not shown) and the mixture-based NL filter (Fig.4) achieved good balance between speckle reduction and small-feature retention. At this high resolution (up to 0.25m) even the boxcar filtered data still carry most of the salient local features. However, as shown in Fig.5, some small-scale features such as the isolated point targets and the double bounce scattering from the sides of buildings are preserved by the mixture-based NL filter to a greater extent.

Disadvantage of the mixture-based NL filter is found in the considerably increased computation time for fitting the mixture model through iterative EM algorithm. Once the mixture model is acquired, the computation load in NL filtering is actually reduced. Dividing the image into smaller blocks allows using less mixture components thus mitigates the computation time to make it viable.

SUMMARY

We introduced a mixture-based non-local filter for polarimetric SAR speckle. The intention is to preserve sharp separation of different scattering mechanisms from the onset. The mixture model fits the speckle globally even when the scene is highly textured such that traditional distributions do not apply. The NL filtering statistically evaluates the similarity of local patterns to admit as many pixels as possible in the filter. Incorporating them together shows a great potential of balancing the contradicting needs between including more pixels and preserving more details.

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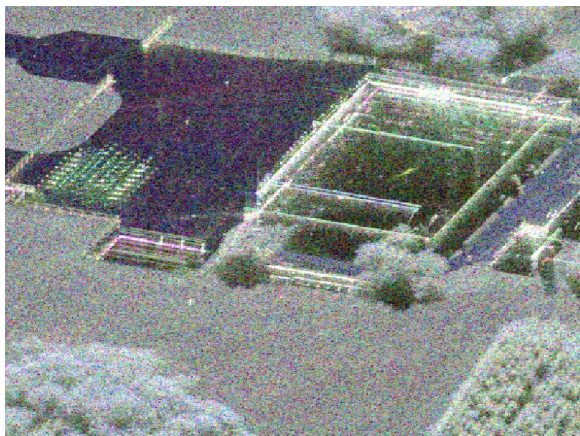


Fig.1 Single look F-SAR image in the Pauli basis composition.

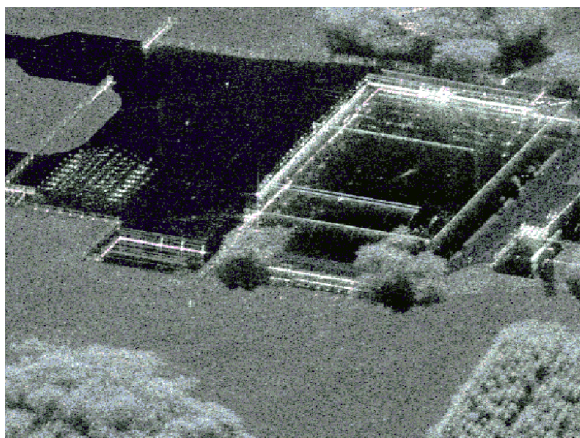


Fig.2 The F-SAR image replaced with mixture components.



Fig.3 Image from diagonal-covariance based NL filtering.

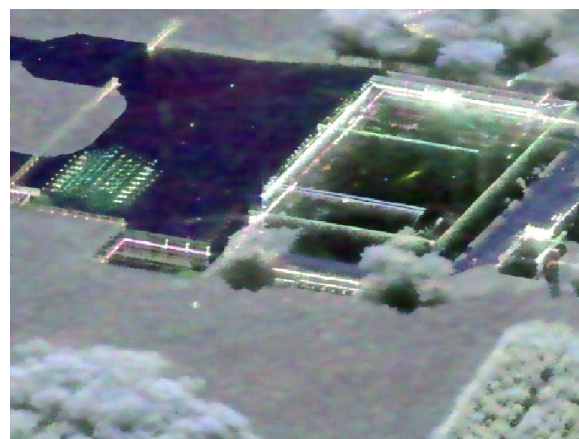


Fig.4 Image from the mixture-based NL filtering.

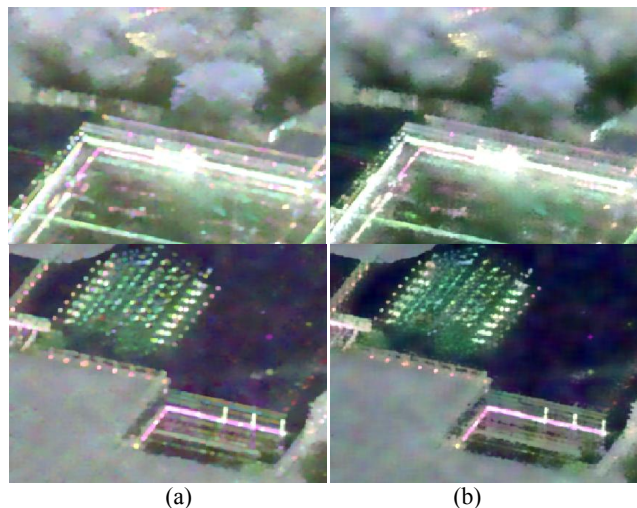


Fig.5 Selected regions from (a) the Wishart-based NL filtering and (b) the mixture-based NL filtering.