Improved Fisher MAP Filter for Despeckling of High-Resolution SAR Images Based on Structural Information Detection

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Abstract

Fisher distribution is a popular model for high-resolution (HR) synthetic aperture radar (SAR) images due to its high-peaked and heavy-tailed characteristics as well as its theoretical justification and mathematical tractability. Based on the Fisher modeling of SAR images, the maximum a posteriori (MAP) filter is suggested. In the Fisher model, the parameter of image looks is thought to be fixed to correspond to the formation mechanism of multi-look intensity images, and the other two parameters are accurately assessed from the SAR image based on second-kind statistics. To improve the Fisher MAP filter especially in the aspect of speckle suppression, the Fisher MAP filter based on recognition of structural information is created using point target detection, the adaptive windowing method, homogeneous region detection, and selection of most homogeneous sub-window. The experiments on despeckling of HR SAR images demonstrate that the improved Fisher MAP filter based on structural information detection can suppress speckle in homogenous and edge regions, and effectively preserve fine details, edges, and point targets.

Keywords: Fisher filter, High-resolution synthetic aperture radar image, Structural information detection, Second-kind statistics

1 Introduction

Synthetic aperture radar (SAR) images are corrupted by speckle, which reduces quality of images and makes the post-processing of images extremely difficult [1]. Therefore, despeckling algorithms are indispensable to accurate understanding of SAR images. For a promising despeckling algorithm, an appropriate distribution of SAR image should be taken into consideration [2-5]. The traditional Rayleigh distribution works well for low-resolution SAR images [6], but it does not perform well on high-resolution (HR) SAR images [6-10]. The log-normal and Weibull distributions are better choices for modeling specific SAR images [11], but they are empirical models, which lack theoretical justification [12-14]. Recently, Fisher distribution, has drawn considerable attention for modeling HR-SAR images, specifically for urban regions, due to its high peak and heavy tail statistical characteristics [15-17]. The Fisher model is strictly derived from the multiplicative model of speckle and the Mellin convolution, owning more theoretical justification and mathematical tractability compared with the log-normal and Weibull [18-19].

In this paper, using Fisher model, the maximum a posteriori (MAP) filter is proposed for high-resolution SAR images. It must be stressed that the parameter of image looks in the Fisher model is fixed, which corresponds to the practical formation mechanism of multi-look intensity images [1]. Under this condition, the Fisher MAP filter only depends on the estimated values of the other two parameters of Fisher model. Recently, a powerful tool called second-kind statistics that relies on the Mellin transformation has been generally exploited to accurately estimate the parameters of some sophisticated distributions for SAR images [18-22]. Motivated by the second-kind statistics, the log-cumulant estimators are presented to accurately estimate the other two parameters of Fisher model from the observed image, and then the Fisher MAP filter can be readily performed. To improve the Fisher MAP filter especially in the aspect of speckle suppression, the Fisher MAP filter based on detection of structural information is constructed. The process includes detection of point target, application of adaptive windowing, detection of the homogeneous region, and selection of the most homogeneous sub-
window [23-25]. We demonstrate the performance of the improved Fisher MAP filter, for despeckling of HR-SAR images. The results show a good trade-off between elimination of speckle and preservation of edges, fine details, and point targets.

2 Fisher Distribution

The probability density function (pdf) of Fisher distribution is defined as:

\[
f(x) = \frac{\Gamma(L + M)}{\Gamma(L) \Gamma(M) \mu^L} \left(1 + \frac{Lx}{M \mu}\right)^{-(L + M)}
\]

(1)

where \( L \) is the image looks, \( M (M > 0) \) is the shape parameter, \( \mu (\mu > 0) \) is the scale parameter, and \( \Gamma(\cdot) \) denotes the Gamma function.

To show the merit of the Fisher distribution in modeling HR-SAR images, a HR-SAR image shown in Figure 1 was modeled by the Fisher distribution as well as other distributions such as Rayleigh, log-normal, and Weibull.

3 Fisher MAP Filter

The general form of the MAP equation is given by

\[
-\frac{1}{X} + \frac{\partial \ln f_x(F)}{\partial X} + \frac{\partial \ln f_x(X)}{\partial X} \bigg|_{X = \hat{X}_{MAP}} = 0
\]

(2)

where \( L \) is the image looks [19]. On the other hand, the true image is modeled by the inverse Gamma distribution, whose pdf is given by

\[
f_x(x) = \frac{L^L x^{L-1} e^{-Lx}}{\Gamma(L)}
\]

(3)

Figure 1. X-Band HR-SAR image (1-m resolution)

The modeling results are presented in Figure 2. The use of logarithmic scale is to detail the fitting degree of various distributions to the tail of image.

Obviously, the HR-SAR image owns the high-peak and heavy-tail characteristics, and only the Fisher distribution can accurately describe such characteristics of high peak and heavy tail simultaneously. Therefore, it is reasonable to believe that the MAP filter that uses Fisher modeling of SAR images performs well especially in preservation of edges and fine details [26-28].

Figure 2. Modeling the SAR image in Figure 1 using various distributions

here \( F \) is the speckle, \( X \) is the true image not corrupted by speckle, \( f_x \) and \( f_x \) are the pdfs of \( F \) and \( X \) respectively, and \( \hat{X}_{MAP} \) is the MAP estimate of \( X \) [29-31].

Obviously, distributions of the speckle and the ground truth image are needed for the MAP formula. In the derivation of Fisher distribution, the Gamma and inverse Gamma distributions are used to describe the speckle and the true image respectively, and then the Fisher MAP equation is constructed according to (2).

For a \( L \)-look intensity image, speckle statistically obeys the Gamma probability distribution, with the following PDF:

\[
f_x(x) = \frac{L^L x^{L-1} e^{-Lx}}{\Gamma(L)}
\]

(3)
\[ f_X(x) = \frac{1}{\Gamma(M)} \left( \frac{M}{\mu} \right)^M x^{-(M+1)} e^{-\frac{M}{\mu}x}, \]  
\[ (1 + L + M) \mu \hat{X} - \mu LY - M = 0, \]

where \( \hat{X} \) is the MAP estimate of \( X \) and \( Y \) denotes the observed image.

Finally, the output of the Fisher MAP filter is straightforward

\[ \hat{X} = \frac{LY + M}{1 + L + M}. \]

Three parameters \( L, M \) and \( \mu \) appear in (6). The parameter \( L \), which appears in the pdf of Gamma distribution for speckle, is closely relevant to the formation mechanism of multi-look intensity images [1]. For a single-look intensity image, speckle is statistically modeled by the exponential distribution. After averaging \( L \) single-look intensity images, a \( L \)-look intensity image is formed, and the speckle in the \( L \)-look intensity image is statistically described by the Gamma probability distribution with \( L \) looks in (3). In fact, the \( L \)-look Gamma distribution is strictly derived from \( L \) convolutions of exponential distribution. Therefore, for a specific \( L \)-look intensity image, the value of \( L \) is fixed and not needed to be estimated [19, 32].

For the use of the Fisher MAP filter, the only parameters \( M \) and \( \mu \) are required to be estimated, which reduces computational load and improves running efficiency of the Fisher MAP filter.

4 Log-cumulant Parameter Estimators Based On Second-kind Statistics

The second-kind statistics are constructed theoretically based on the Mellin transformation [33-34]. Denoting \( f \) as a pdf defined in \([0, \infty)\), the second-kind statistics are defined successively as follows, including the second-kind first characteristic function \( \Phi(s) \) and the second characteristic function \( \psi(s) \), and the \( r \)-th order log-cumulant \( \hat{k}_r \) [31]:

\[ \Phi(s) = \int_0^\infty x^{s-1} f(x) dx, \]
\[ \psi(s) = \ln \Phi(s), \]
\[ \hat{k}_r = \frac{d^r \psi(s)}{ds^r} \bigg|_{s=1}. \]

The log-cumulants \( \hat{k}_1 \) and \( \hat{k}_2 \) can be computed from the observed samples \( y_i \) as

\[ \hat{k}_1 = \frac{1}{N} \sum_{i=1}^N \ln y_i, \quad \hat{k}_2 = \frac{1}{N-1} \sum_{i=1}^N (\ln y_i - \hat{k}_1)^2. \]

Here, \( N \) is the number of samples. The widely used multiplicative model of speckle is given by [28]

\[ Y = F \cdot X, \]

where \( Y \) is the observed image, \( F \) is the speckle, and \( X \) is the true image. It is demonstrated that the log-cumulant of any order of \( Y \) is defined by the sum of the log-cumulant of the same order of \( F \) and \( X \) [31].

Particularly, the first two log-cumulants of \( Y \) can be specified by

\[ \hat{k}_{y(1)} = \hat{k}_{f(1)} + \hat{k}_{x(1)}, \quad \hat{k}_{y(2)} = \hat{k}_{f(2)} + \hat{k}_{x(2)}. \]

Here, \( \hat{k}_{y(1)} \) and \( \hat{k}_{y(2)} \) can be assessed empirically from the image based on Eq. (10). Obviously, the parameters \( M \) and \( \mu \) required for the Fisher MAP filter can be estimated from the image. Recalling the construction of the Fisher MAP filter, the speckle and the ground truth image are modeled by the Gamma and inverse Gamma distributions, respectively. Substituting (3) into (7), (8), and (9) successively, the first two log-cumulants of speckle are given by

\[ \hat{k}_{f(1)} = \psi(L) - \ln L, \quad \hat{k}_{f(2)} = \psi(1, L), \]

where \( \psi(\cdot) \) denotes the Digamma function, and \( \psi(1, L) \) denotes the Trigamma function [31].

Similarly, the first two log-cumulants of the true image are derived by

\[ \hat{k}_{x(1)} = \ln \left( \frac{M}{\mu} \right) - \psi(M), \quad \hat{k}_{x(2)} = \psi(1, M). \]

Substituting (13) and (14) into (12), \( M \) and \( \mu \) can be estimated as:

\[ \psi(1, \hat{M}) = \hat{k}_{y(2)} - \psi(1, L), \]
\[ \hat{\mu} = \frac{\hat{M}}{\psi(\hat{k}_{y(1)} - \psi(M) - \psi(L) + \ln L)}. \]

Here, \( \hat{k}_{y(1)} \) and \( \hat{k}_{y(2)} \) are the estimated values of the first two log-cumulants of \( Y \) respectively, which are calculated from the observe image by using Eq. (10).

As the Trigamma function \( \psi(\cdot, \cdot) \) is monotonous, the shape parameter \( M \) can be estimated from Eq. (15) by using bisection [34], and the scale parameter \( \mu \) can be readily computed by Eq. (16).
5 Improved Fisher MAP Filter Based On Structural Information Detection

Based on structural information, the Fisher MAP filter is improved to yield better balance between speckle suppression and structural information (i.e., edges, fine details, and point targets) preservation [23]. The structure diagram of the improved Fisher MAP filter is provided in Figure 3.

- Current region
- Point target detection
- Point target
- Region without point target
- Adaptive windowing
- Region classification
- Edge region
- Sub-window detection
- Most homogeneous sub-window
- Preserve point target
- Fisher MAP filter
- Box filter

Figure 3. Structure chart of the improved Fisher MAP filter that uses structural information detection

The algorithm starts from the smallest 3 by 3 window for each pixel of image. Firstly, the point target is found by comparing the coefficient of variation (CoV) with the upper threshold. If the CoV is greater than the upper threshold, the point target appears, and its value is directly preserved. Next, the adaptive windowing is adopted to get the size of sliding window. The size of window is gradually adjusted by comparing the CoV of boundary pixels in a current window with the adaptive threshold. When the CoV is smaller than the threshold, the current window enlarges until it meets the predefined maximum window.

Finally, the sliding window to which the adaptive windowing method leads is classified by its heterogeneity. If sliding window belongs to heterogeneous regions where edges and fine details appear, sliding window is divided into eight directional sub-windows. By calculating the coefficient of variation for each sub-window, the most homogeneous sub-window with the lowest variation coefficient is chosen as the filtering region, which tends to efficiently suppress speckle in edge regions. Obviously, the improved Fisher MAP filter based on structural information detection can lead to better performance in comparison with the fixed-size Fisher MAP filter.

6 Despeckling Experiments

The improved Fisher MAP filter based on structural information detection was tested on two HR-SAR images. The SAR image and its despeckling results are shown in Figure 4. The classical Gamma MAP filter based on Gamma prior distribution was provided for comparison [26, 35]. The performance of various filters is evaluated in Table 1. ENL is the equivalent number of looks, and bigger values of ENL denote stronger speckle suppression [36-37]. DCV is defined by the difference of coefficient of variations between the filtered image and the true image in an edge region. Smaller values of DCV denote better edge preservation [38-67].

![Original SAR image](image1.png)  ![Gamma MAP filter (5 by 5 window)](image2.png)

![Fisher MAP filter (5 by 5 window)](image3.png)  ![Improved Fisher MAP filter (3 by 3 minimum window and 11 by 11 maximum window)](image4.png)

Figure 4. Despeckling results

Obviously, the Fisher MAP filter preserves edges, fine details, and point targets are much better when compared to the Gamma MAP filter, at the cost of some speckle that still exists in homogeneous regions.
and in edge regions. Integrating the effective preservation of edges, fine details, and point targets with the sufficient speckle suppression, the improved Fisher MAP filter based on structural information detection achieves the best performance that yields the biggest ENL and the smallest DCV.

The second SAR image and its despeckling results are given in Figure 5. The speckle pattern shown in Figure 6 is used to evaluate filter performance [27, 29]. Obviously, compared to the fixed-size Fisher MAP filter, the improved Fisher MAP filter based on structural information detection preserves edges and smoothes the speckle effectively.

![Original SAR image](image1) ![Fisher MAP filter](image2) ![Improved Fisher MAP filter](image3)

**Figure 5.** Despeckling results

![Speckle pattern](image4)

**Figure 6.** Speckle pattern corresponding to Figure 5

<table>
<thead>
<tr>
<th>Filter</th>
<th>ENL</th>
<th>DCV</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gamma MAP filter</td>
<td>96.2423</td>
<td>0.4635</td>
</tr>
<tr>
<td>Fisher MAP filter</td>
<td>52.9435</td>
<td>0.4547</td>
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<tr>
<td>Improved Fisher MAP filter</td>
<td>122.9742</td>
<td>0.4491</td>
</tr>
</tbody>
</table>

**Table 1.** Quantitative measures evaluating various filters in Figure 4

7 Conclusion

Due to its high-peaked and heavy-tailed characteristics as well as its theoretical justification and mathematical tractability, the Fisher distribution is a popular choice for modeling HR-SAR images. Here, a Fisher MAP filter based on the Fisher model has been suggested. In this model, the parameter of image is regarded to be fixed to correspond to the formation mechanism of multi-look intensity images, and the other two parameters are accurately estimated from the image based on the second-kind statistics. In order to enhance the performance of the Fisher MAP filter especially in the aspect of speckle suppression, the Fisher MAP filter based on structural information detection has been proposed. The improved Fisher MAP filter, which successively performs the point target detection, the adaptive windowing, the homogeneous region detection, and the selection of the most homogeneous sub-window, leads to well-balanced performance between speckle suppression and edge detection. Despeckling experiments on HR-SAR images demonstrate that, compared to the fixed-size Fisher MAP filter, the proposed improved Fisher MAP filter based on structural information detection can preserve edges, fine details, and point targets more effectively, and is able to subdue speckle in homogeneous and edge regions much more sufficiently.

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Declaration of Interest

The authors have no interest to declare.

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Biographies

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