Abstract

Speckle is a granular disturbance, usually modeled as a multiplicative noise that affects synthetic aperture radar (SAR) images, as well as all coherent images. Over the last three decades, several methods have been proposed for the reduction of speckle, or despeckling, in SAR images. The experiment starts with the linear filtering, non-linear filtering, adaptive filtering, and hybrid filtering. Though the classical linear filtering methods have lower performance comparatively, the hybridization between them outperforms than the recently proposed methods. However, the careful selection of such filters and their influencing order highly affects the performance of such filtering approaches. In this paper, a hybrid filtering is proposed for SAR despeckling, which comprises the improved versions of frost and mean filter. The performance of the proposed system is analyzed and compared with the recently SAR despeckling methods. The results indicate that the hybrid filters are competitive as they are able to despeckle the SAR images better than the existing techniques.

1. INTRODUCTION

Synthetic Aperture Radar (SAR) imaging is more suitable for different climate conditions [1] than the optical remote sensing. However, the major problem in SAR imaging is the presence of speckle, a signal dependent granular noise, which degrades the quality and analysis of the image. Hence, it is important to reduce the speckles from the SAR images before the image analysis starts, at the same time, the image details such as target points, textures, shapes should not be get disturbed. Over the last decades
there are numerous research contribution on despeckling, as the new generation of SAR imaging has naturally gains the attention of researchers towards this problem. The concept of despeckling algorithm is closely related with Additive White Gaussian Noise (AWGN) denoising. However, the speckle noise is multiplicative in nature; the log-transformation is applied on the signals to convert them into additive to fit the approaches with additive noise filtering procedure. There are three categories of despeckling algorithms (i) spatial, (ii) wavelet-based, and (iii) nonlocal filtering.

The spatial filtering techniques take a small kernel and replace the target pixel of the window by means of a weighted average. For a low-pass filter, where the weights are equal, not only reduces the noise but also disrupts the edges, structures and textures. Considering the multiple observation of the same signal is one solution to this problem, and the weights must be estimated based on statistical models of signal and noise and, the local statistics of the image. Though the improved spatial-filters offers better despeckling, distinguishing homogeneous regions from texture or edges is a difficult task. [22, 23]. Filtering in frequency domain is well-suited for SAR images as small number of coefficients is enough to capture most of the signal content. It is studied in the literature that the wavelet based methods are safe for SAR despeckling as it guarantees improved performance than the spatial filters. Moreover, the wavelet based filters are shift, rotation and scale invariant. But, disturbs in edges and the heterogeneous regions makes the SAR images visually annoying in some cases. Nonlocal filtering is the recent approach follows the concept of spatial filtering [31]. Here the kernel & the target pixel are chosen as spatial-filter does, but the difference is that the weighted average is estimated with the similar kernels surrounding the target pixel. Nonlocal Means (NLM) algorithm proved its efficiency and spawned intense research. This idea is further developed in block-matching 3-D (BM3D) [32] where only a few pixels with the most similar context are used for the estimation. Obviously, the kernel selection is influenced by noise itself, especially in flat areas of the image, which can be dangerously self-referential. In general, hybrid filtering is another approach which always exists in the race, also competitive. Careful selection of filters and their pipelining order defines the performance of the approach. In this paper a hybrid filtering approach with frost and mean filters to construct a filter which comprises of all the two filters strengths and to overcome ones drawback with others.

The rest of the paper is described as follows: the following section describes the background of filtering methods to be hybrid later. Section 3 explains the proposed hybrid filter. Section 4 presents the numerical results and analyzes the performance of the hybrid filter. Section 5 concludes the paper.

2. EXISTING FILTERING TECHNIQUES

2.1 Edge based Adaptive Mean Filter

Some adaptive filters, such as the Kuan, Lee, minimum mean square error (MMSE) and Frost filters, have been tested on synthetic aperture radar (SAR) data without considering the level of homogeneity in the pixels. Therefore, they degrade the spatial resolution of images and smooth details, while also decreasing the speckle noise level. Shamsoddini and Trinder (2012) proposed the use of the standard deviation of the edge map and the Coefficient of Variation (CoV) to detect isolated points, edges and texture areas, and homogeneous areas.

The method developed in this article has been based on three thresholds V, determined from the standard deviation map derived within a 5 × 5 window, but the window can be larger. Initially, a moving 5 × 5 window is used to generate a new criterion for separating different textural areas in a noisy SAR image. Each 5 × 5 window can be divided into nine 3 × 3 sub-windows and the mean values for each sub-
window, called ‘sub-mean’, are calculated. Then, four 3 × 3 edge-detection filters are separately scanned over the submean windows as follows:

\[
\begin{bmatrix}
-1 & 0 & 1 \\
-1 & 0 & 1 \\
-1 & 0 & 1 \\
\end{bmatrix}
\begin{bmatrix}
0 & 1 & 0 \\
-1 & 0 & 1 \\
0 & 0 & 1 \\
\end{bmatrix}
\begin{bmatrix}
1 & 1 & 1 \\
1 & 1 & 1 \\
1 & 0 & -1 \\
\end{bmatrix}
\]

According to Lee and Pottier (2009), these filters are affected by speckle noise less than other filters such as the Sobel filter. Then, the results are summed and set to absolute values whose standard deviations can provide textural information for different parts of a SAR image. This leads to two criteria for classifying the image into different parts according to texture information: the previously derived coefficient of variation map defined by parameters $C_{ij}$ and this new standard deviation map, values of which are described by parameters $V$.

The non-edge areas are divided into two sub-classes: the sub-class which includes pixels with standard deviation values less than or equal to $V_{NE}$ is smoothed by a mean filter; the second sub-class comprising pixels with standard deviation values between $V_{NE}$ and $V_{NE_{-max}}$ and describing potential isolated point scatterers should be further divided into two sub-groups:

- pixels whose coefficients of variation are less than or equal to $C_{max}$ and
- pixels with coefficients of variation higher than $C_{max}$

For the first sub-group, the mean value of pixels within the selected window is used as the filtered pixel value because they are considered to be in the non-edge class and using the mean value does not degrade the spatial information. The second sub-group represents isolated points and their surrounding pixels. One of the most important problems with existing filters is that they consider the neighboring pixels of point scatterers in the same way as the point scatterers themselves. This is because the coefficient of variation is not a reliable criterion for these pixels and hence is unable to separate them from the central point scatterer. In order to solve this problem and to filter these pixels, Qiu et al., (2004) developed an algorithm, called the Point Scatterer Discriminator (PSD). This algorithm is based on the assumption that the differences of pixel values between point scatterers and their neighbors are high. The algorithm involves two steps providing that the pixel is not identified as a point scatterer in the first step. After labeling a pixel as a candidate point scatterer, having a coefficient of variation higher or equal to $C_{max}$, a 3 × 3 window is centered on this point. Then, the maximum and minimum pixel values of this window are selected and a $D$ value is calculated by executing the following equation on all pixels within the window:

\[
D = \frac{DN_{\text{max}} - DN_{ij}}{DN_{\text{max}} - DN_{\text{min}}}
\]

Where $DN_{\text{max}}$ is the highest pixel value within selected window, $DN_{\text{min}}$ represents the lowest value within selected window and $DN_{ij}$ is the pixel value of pixel $(i,j)$. Then the median and mean values for the matrix of $D$ values are calculated and the larger value, $M$, is used to make a decision about the central pixel. If the central value of the matrix of differences is less than $M$, then this pixel is known as a point scatterer and the process is terminated; otherwise, in the second step, the pixel whose $D$ value is more than or equal to $M$ is selected and the coefficient of variation for this pixel is calculated. Since this sub-class is only expected to include point scatterers, and no other textural information, this pixel is known as a point scatterer provided its coefficient of variation is higher than $C_u$ and its value is maintained; otherwise the mean value of the selected pixels is assigned as the filtered pixel value. Some isolated points with very low pixel values may also be preserved using this algorithm. These points would not be recognized as point scatterers in the first step of this algorithm.
Filtering of edge areas is more complicated than the other classes because these areas include textural information such as edges and other features derived from built-up areas. Therefore, using the mean value over this class causes smoothing of the textural information and a degradation of the image details; however, there will still be some homogeneous areas within this class that should be smoothed using a mean filter, as well as some point scatterers that should be preserved. Pixels whose coefficients of variation $C$ are between $C_u$ and $C_{max}$ require the most complicated filtering because they display edges and textured details.

After selecting such pixels, the following equation, called the Homogeneity Likelihood (HL), is applied to find pixels of similar homogeneity within a $5 \times 5$ window:

$$HL = \frac{C_c - C_{ij}}{C_{max} - C_{ij}}$$

where $C_c$ is the coefficient of variation of the central pixel and $C_{ij}$ represents the coefficient of variation for pixels within the window. This index shows the similarity between the central pixel and neighboring pixels, which are not based on a fully developed speckle model; the lower the value of a pixel, the higher the similarity with the central pixel in terms of speckle model. Then this index is used to weight pixels using the following expression:

$$\begin{cases} 
  w_{ij} = \exp\left(-HL\right) & \text{if } C_u < C_{ij} < C_{max} \\
  w_{ij} = 0 & \text{if } C_{ij} \leq C_u \text{ or } C_{max} \leq C_{ij}
\end{cases}$$

The weighted mean value, $Z_w$, is calculated as follows:

$$Z_w = \frac{\sum_{i} \sum_{j} w_{ij} Z_{ij}}{W}$$

where $Z_{ij}$ is the pixel value at $(i,j)$. $W$, which is calculated as follows, is used to normalize the weighting factors:

$$W = \sum_{i} \sum_{j} w_{ij}$$

The coefficient of variation is calculated for selected pixels whose preliminary coefficients of variation are between $C_u$ and $C_{max}$. If this value is less than or equal to $C_u$, the filtered value is equal to the weighted mean value, while if it is higher than $C_{max}$ the original value is preserved. For the pixels whose new coefficients of variation are between $C_u$ and $C_{max}$, the filtering method is as follows:

Filtered Pixel = $Z_w B + Z (1 - B)$

where $B$ is calculated according to the following equation:

$$B = \exp\left(-KN\right)$$

$K$ represents a damping factor and $N$ is calculated as follows:

$$N = \frac{C_{Sij} - C_u}{C_{max} - C_{Sij}}$$

where $C_{Sij}$ is the coefficient of variation for selected pixels. This equation means that the more heterogeneous the pixels are the less filtering is required. It is apparent that above equations are similar to the equations that for the enhanced Lee filter, but the differences are the inclusion of the weighted mean instead of simple averaging and the application of the coefficient of variation for the selected pixels instead of for all pixels within the window.

Pixels that have values more than or equal to $V_{E,max}$ in the standard deviation map may be categorized as point scatterer candidates because some of them are pixels surrounding point scatterer pixels. Therefore, it is necessary to use the PSD algorithm to find which pixels are really point scatterers. For the pixels which are not found to be point scatterers, the filtered pixel value is determined from the average value.
2.2 Adaptive Frost Filtering

A Frost filtering algorithm of SAR images with adaptive windowing and adaptive tuning factor is proposed to resolve the problem that the traditional Frost filtering algorithm cannot balance speckle suppression and edge preservation effectively. The tuning factor and the window influence the performance of the Frost filter significantly. Similar to the Lee filter and the Kuan filter, the Frost filter (Frost et al., 1982) is also based on the minimum mean square error criterion. However, the Frost filter does not own the simple linear weighted form by the means of the real image and the observed image. It is assumed that the impulse response of the system is constant under the conditions of limited bandwidth, and the actual image is estimated by the convolution of the observed image and the corresponding impulse. Finally, the filter equations can be derived by the minimum mean square error criterion. The Frost filter can be expressed as (Zengguo, 2012)

\[ I(i,j) = \frac{\sum_{s} \sum_{h} P_{sh} m_{sh}}{\sum_{s} \sum_{h} m_{sh}} = e^{-KCf_{sh}} 
\]

where \((i,j)\) is the location of current pixel, \(I(i,j)\), denotes the output of the filter, \(P_{sh}\) denotes the values of pixels among the window centered at \((i,j)\), \(K (K > 0)\) is the tuning factor, \(Cf\) is the coefficient of variation that is defined by the ratio of the sample standard deviation to the sample mean, and \(d_{sh}\) is the distance between any pixel in the current window to the current pixel. Obviously, the value of the tuning factor \(K\) is important for the performance of the Frost filter. When the value of \(K\) is small, the Frost filter can suppress speckle well, but it cannot preserve edges and fine details effectively. As the value of \(K\) increases, the ability of speckle suppression of the Frost filter is getting worse, but the edge preserving has gradually improved.

Since the tuning factor in the Frost filter is important but not easy to predefined, a modified Frost filter based on adaptive tuning factor was proposed in (Zia and Wang, 2011). This method computes the tuning factor adaptively by using the regional characteristics and the values of region pixels simultaneously. The centered pixel in current window is contaminated by speckle, and, in some degree, the degree of such contamination depends on whether the centered pixel is the most representative in current window. The t statistics were used to measure the representative of the centered pixel, because the sample mean and sample variance for t statistics can be estimated by the mean and variance of all pixels in current window (Zia and Wang, 2011). In another word, the statistics were adopted to measure the degree of speckle contamination for the centered pixel, and then the adaptive tuning factor was constructed as follows:

\[ K(s,h) = T(t_{0}) \cdot Q(s,h) \]

\[ T(t_{0}) = \frac{|I(t_{0}) - u(t_{0})|}{\delta(t_{0})} \]

\[ Q(s,h) = \frac{1}{(2N+1)^2} \sum_{i=-N}^{N} \sum_{j=-N}^{N} \frac{|I(s,h) - I(t_{0})|}{\sum_{i=-N}^{N} \sum_{j=-N}^{N} |I(m,n) - I(t_{0})|} \]

Here, \(K(s,h)\), is the adaptive tuning factor that is composed of the t statistic value \(T(t_{0})\) and the gray characteristics of neighborhood pixels \(Q(s,h)\), \(I(t_{0})\) is the centered pixel value, \(u(t_{0})\) and \(\delta(t_{0})\) are the mean and the standard deviation of the pixels in current window centered at \(t_{0}\), respectively. The square window is used, and the size of window is denoted as \(N\). Obviously, the above tuning factor is adaptively adjusted based on regional characteristics, leading to better performance of the Frost filter in comparison with the fixed tuning factor used in the traditional Frost filter. Zhihua and Zengguo (2015) further improve the modified Frost filter with the adaptive tuning factor by using the adaptive windowing. The size of window is not fixed but adjusted adaptively according to regional characteristics.
The proposed double-adaptive Frost filter is demonstrated to own better trade-off between speckle suppression and edge preservation. The adaptive windowing method was proposed to overcome the limitation of the traditional filters using the fixed-sized window (Park et al., 1999; Zengguo and Han, 2010). For the adaptive windowing, the size of window is not fixed but adaptively adjusted based on regional characteristics. In order to save computational load, only the boundary pixels of the current window are used to determine the size of the next window. Denoting \((i,j)\), as the location of the current pixel, the coefficient of variation and the threshold are defined in current window as follows:

\[
C_{ij} = \frac{\sigma_{ij}}{m_{ij}},
\]

\[
T_{ij} = \eta \left[ 1 + \frac{1 + 2\sigma_{ij}^2}{\sqrt{8(W_{ij} - 1)}} \right],
\]

Here, \(\sigma_{ij}\) and \(m_{ij}\) are the sample standard deviation and the sample mean respectively, which are defined on the boundary pixels of the current window. \(T_{ij}\) is a threshold that determines the smoothness of the processed images. \(\sigma_{ij}^2\) and \(W_{ij}\) are the variance of speckle and the window size, respectively. \(\eta\) is a system parameter whose value is recommended as [12]. Finally, the size of window centered at \((i, j)\), is adaptively adjusted as follows:

\[
W_{ij} = \begin{cases} 
\min \{W_{ij} + 2, W_{\max}\}, & \text{if } C_{ij} \leq T_{ij} \\
\max \{W_{ij} + 2, W_{\min}\}, & \text{if } C_{ij} > T_{ij}
\end{cases}
\]

Here, \(W_{\max}\) and \(W_{\min}\) denote the maximum and the minimum window size, respectively. In order to improve the running efficiency, the adaptive windowing starts with the smallest window. For current window, the coefficient of variation \(C_i\) and the threshold \(T_i\) are calculated respectively. If \(C_i\) is not larger than \(T_i\), the size of window gradually increases until an appropriate size of sliding window is obtained. This means that the size of window depends on the regional characteristics. For homogeneous regions, a large window is usually obtained to suppress speckle well. For heterogeneous regions, a small window is obtained to effectively preserve edges. Finally, for the window that the adaptive windowing method yields, its heterogeneity is detected by comparing the variation coefficient of this window with the speckle variation coefficient. If the variation coefficient of the window is smaller than the speckle variation coefficient, the window belongs to a homogenous region, and the box filter is directly used to suppress speckle sufficiently.

Obviously, due to the adaptive choice of window size, speckle suppression and edge preservation are well balanced. In a word, the proposed double-adaptive Frost filter includes three parts. Firstly, an appropriate window size is achieved by using the adaptive windowing method. Secondly, the heterogeneity of this window is detected and the box filter is used for the homogeneous region. Finally, the modified Frost filter with adaptive tuning factor is used.

### 2.3 Merits & Demerits of Existing Filtering

Among the spatial filters the mean and the median filter are simple. However, the mean filter degrades spatial resolution as the multi-look processing technique does. The most well-known and widely used image-domain speckle filter is the local statistics adaptive filter proposed by Lee (1980, 1981). The Lee filter uses local statistics such as mean and standard deviation on a fixed-size window to determine different weight factors for smoothing. In a homogeneous region the filtered output value is the linear average of pixels in the neighborhood, whereas in an extremely busy region, the output becomes the value of the input pixel itself. Mansourpour et al., (2006) compared the speckle noise reduction methods and among all studies the effect of mean, median, Lee sigma, local region, Lee, Gamma-MAP, and Frost...
filters with different kernel sizes on both simulated and real imageries. In both simulated and real imageries it is seen that regardless of the kernel size, Mean, Median and Local Region filters perform poorly. The numerical results show that Gamma-MAP filter performs much better for preserving the edge information. In the case of real SAR imagery, the Gamma-MAP, Frost, and Lee filters with a 5x5 kernel show better results as the differences of their Means from the Mean of original image is low while they all have low Standard Deviation. Serkan et al., (2008) studied a speckle reduction algorithm by using the Edge Map-Directed Adaptive Mean (EMDAM) filter. It adapts the ordinary mean filter according to the scene heterogeneity. Edge-crossing maps determined by an edge detector are used to find the largest homogeneous subregion in the moving filter window. Then, the mean filter is adapted only to this homogeneous part of the moving filter window and applied if no edge crossing is found. The filter performance was assessed both quantitatively and qualitatively. It is found that the EMDAM filter preserves textures and details while reducing speckle to a desired level. The Mean Filter is a simple one and does not remove the speckles but averages it into the data. Generally speaking, this is the least satisfactory method of speckle noise reduction as it results in loss of detail and resolution. However, it can be used for applications where resolution is not the first concern.

Many adaptive filters for SAR image denoising have been proposed in the past. The simplest approaches to speckle reduction are based on temporal averaging, median filtering, and Wiener filtering. The classical Wiener filter, which utilizes the second-order statistics of the Fourier decomposition, is not adequate for removing speckle since it is designed mainly for additive noise suppression. To address the multiplicative nature of speckle noise, Jain developed a homomorphic approach, which, by taking the logarithm of the image, converts the multiplicative into additive noise, and consequently applies the Wiener filter (Jain, 1989). The Frost filter was designed as an adaptive Wiener filter that assumed an autoregressive (AR) exponential model for the scene reflectivity (Achim et al., 2006). The Frost filter was designed as an adaptive Wiener filter that assumed an autoregressive (AR) exponential model for the scene reflectivity (Achim et al., 2006). The BM3-D algorithm (Dabov et al., 2007) operates a very effective synthesis of all these ideas. It works in two steps: The first one uses hard thresholding to build a relatively clean image for estimating statistics, while the second one performs the actual denoising through empirical Wiener filtering in the transform domain. Both steps, however, work not on local neighborhoods but on groups of blocks drawn from different image locations and collected on the basis of their similarity, in the spirit of the nonlocal approach. Therefore, the resulting 3-D groups are highly redundant, allowing for a sparser WT representation and a more effective separation between signal and noise through hard thresholding in the first step; as a further consequence, statistics can be more reliably estimated, and the Wiener filtering of the second step turns out to be extremely effective. Solbo and Eltoft (2008) developed a Wiener-type speckle filter that operates in the stationary wavelet domain called Stationary Wavelet-domain Wiener (SWW) speckle filter. This filter works on non-overlapping blocks in the wavelet domain, which are obtained by a quadtree algorithm. Due to the dyadic support of the wavelet coefficients, a natural smoothing is carried out on the boundaries between neighboring blocks, and no visual boundary effects can be observed.

The following table summarizes the characteristics of frost and mean filters.

<table>
<thead>
<tr>
<th>Filter</th>
<th>Frost Filter</th>
<th>Mean Filter</th>
</tr>
</thead>
<tbody>
<tr>
<td>Merits</td>
<td>Linear filter</td>
<td>Non-linear</td>
</tr>
<tr>
<td></td>
<td>Additive Noise</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Adaptive filtering</td>
<td>Smoothing</td>
</tr>
<tr>
<td>Demerits</td>
<td>Not suitable for speckle Noise</td>
<td>Can’t preserve edges</td>
</tr>
</tbody>
</table>

3. THE PROPOSED HYBRID FILTERING
There is another approach of filtering called hybrid filter, used to merge more than one filters together to inherit the advantage of all. Shanthi and Valarmathi (2011) proposed an algorithm using Hybrid order statistics filter- HMM (Hybrid Mean Median) is proposed, which is a combination of mean and median filters to suppress speckle noise in SAR color images. The performance metrics shows that the proposed filter performs better in terms of PSNR and MSE. Bhateja et al., (2014) proposed an improved local statistics filter for filtering the speckle noise from the SAR images. The proposed filter is a combination of mean and hybrid median filters, employing a novel 7x7 filtering template. The performance of the proposed filter is tested against the standard Hybrid Median filters for which the evaluated values show better performs in terms of PSNR and SSI. Also, this filter has a novelistic property of removing noise, alongside edge retention and details preservation. Zheng et al., (2014) proposed an unsupervised change detection technique by using k-means clustering on the combined difference image. This method uses the local consistency of the difference image after using the mean filter and the edge information preservation of the difference image after using the median filter for better difference image representation.

The main idea of this paper is to hybrid these filters to take all their advantages while the demerits of each filter could be resolved by the merits of another. For the hybridization the improved versions of mean, median and frost filters such as Edge based Adaptive Mean (EAM) filter (Shamsoddini and Trinder, 2012), and the Adaptive Frost (AF) filter (Zhihua and Zengguo, 2015) are used. Hence the hybridization filter is Linear, Adaptive, Preserve the edges, suitable for speckle noise and also smoothen the images. In this paper, the above discussed filters are hybrid together for SAR despeckling.

The steps involved in the proposed algorithm is

- Initially the image is applied with log-transformation to convert the multiplicative noise into additive, now the signal is suitable for the first step of filtering where the Adaptive Frost filter is applied.
- Finally for the overall smoothing, the EAM filtering is applied to avoid the ridges caused by previous filtering at homogeneous regions.

4. EXPERIMENTS & RESULTS

The proposed framework is studied with both real and simulated SAR images. And their performance is studied with three different performance measures like PSNR (Peak Signal-to-Noise Ratio, Signal to Clutter Ratio, and Edge Preservation Index). The following figure shows the results of the hybrid filter from simulated and real images.
PSNR 27.8832  29.1152
SCR 4.1407  4.2187
EPI 0.5055  0.8043

Figure 2. Despeckling Results of Hybrid Filter with Simulated SAR Image (a) Original Image, (b) Noisy Image, (c) Adaptive Frost Filter Result, (d) AF+EAM Filter Result

Further the proposed hybrid filter is compared with the four other existing despeckling approaches (BM3D (Dabov et al., 2007), SWW (Solbo&Eltoft, 2008), Frost Filter (Achim et al., 2006), Mean-Median (Bhateja et al., 2014). Table 1 quantifies performance comparison of despeckling methods. The results indicate that the hybrid filter outperforms the existing approaches.

Table 1. Performance Comparison of Despeckling Methods

5. CONCLUSIONS

Synthetic Aperture Radar (SAR) imaging is affected by speckle noise in nature, which makes its interpretation harder. Numerous filtering methods like spatial filtering, frequency-domain filtering, non-local filtering and hybrid filtering approaches are presented in the literature. Among these the non-local mean filtering outperforms recent days, and hybrid filters produces similar results as NLM filters. This paper proposes a hybrid filter for SAR despeckling, where the Frost and Mean filters are put together for constructing a novel hybridization called Hybrid Filter. The SAR images are applied with these filters one-by-one serially and the result in analyzed and compared with the other denoising methods. The results indicate that the proposed Hybrid filter has superior performance than the existing filters in the spatial, frequency, hybrid as well as non-local domains.

References


