# IMAGE TEXTURE PRESERVATION IN SPECKLE NOISE SUPPRESSION

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**KEY WORDS:** SAR, Image, Radar, Texture, Edge, Detection, Model

**ABSTRACT:**

Speckle noise which occurs due to the coherent imaging system is the best known problem of SAR images and in turn, affects classification, change detection, biomass estimation and interpretation results. Several adaptive filtering methods have been documented to deal with this issue, such as Kuan, Lee, MMSE and Frost filters. These filters do not consider the level of homogeneity in the intensity of the pixels. For this reason, they degrade the spatial resolution of image and smooth details, while significantly decreasing the speckle noise level. There are other filters such as Enhanced Lee and Gamma Map that utilize the level of homogeneity, but they cannot adequately suppress speckle noise. Moreover, pixels whose coefficients of variation are near to maximum and minimum threshold values are not correctly filtered using these filters. In addition to these weaknesses, pixels surrounding a point scatterer are also treated as point scatterers due to shortcoming of the method of evaluating the coefficient of variation for differentiating between them and the point scatterer. We have developed a new method based on the homogeneity level for speckle noise suppression and simultaneously edge and feature preservation. Also, an algorithm has been proposed based on local statistical information to filter the pixels surrounding point scatterers. The results show an improvement in speckle reduction and texture preservation as well as reduction in the number of unfiltered pixels.

## 1. INTRODUCTION

Speckle noise, also referred to as 'speckle' is common to all imaging systems which utilize a coherent mechanism to acquire images, and SAR images are no exception (Bamler, 2000). In coherent systems, backscatter signals add to each other coherently and random interference of electromagnetic signals causes the speckle noise to occur in the image (Saevarsson et al., 2004). In fact, speckle is multiplicative noise that alters the real intensity values of features in a scene (Dong et al., 2001). Hence, speckle reduces the potential of SAR images to be utilized as effective data in remote sensing applications such as classification and segmentation, change detection, biomass estimation and interpretation, due to a degradation in appearance, quality and the recorded power of returns (Ali et al., 2008; Lee and Pottier, 2009). For this reason, speckle reduction becomes one of the more important tasks in radar remote sensing.

The main requirements that speckle suppression methods must meet are speckle reduction, and edge or texture preservation (Dong et al., 2001). In homogeneous areas filtering should only reduce the speckle noise level. A minimum unbiased estimator such as mean filter or box filter can perform very well and efficiently reduce speckle noise level over these areas (Lopes et al., 1990 b). Conversely, in the more heterogeneous areas, an ideal filter should suppress speckle noise and simultaneously preserve the edges and features, so a mean filter is not reliable for this type of data. According to these considerations, a good adaptive filter should have two important characteristics; first it should use an efficient discriminator to separate the speckle from the textural information and secondly, the filter should adaptively deal with speckle noise based on the type of speckle noise model which it follows (Lopes et al., 1990 b).

In general, speckle noise filters are grouped into two main categories:

- Statistical filters that use a priori statistical knowledge about speckle noise, the most common being Lee (Lee, 1981), Frost (Frost et al., 1982), Kuan (Kuan et al., 1985). These filters smooth speckle adequately, but they do not preserve details efficiently. Other statistical filters maintain feature information at the cost of poor speckle noise reduction, such as the Gamma Map (Lopes et al., 1990 a) and Enhanced Lee (Lopes et al., 1990 b) filters while all of the mentioned filters are based on speckle models. In addition, the latter filters are not able to filter large parts of images where the coefficient of variation is weak as explained later. There are other statistical filters such as mean and median filters which are not based on speckle models.
- frequency domain methods, such as Wavelet and Fourier transformations (Dong et al., 2001; Saevarsson et al., 2004; Maycock et al., 2007). These filters are not based on speckle models.

In this paper we aimed to develop a filtering method that can reduce the speckle noise and at the same time preserve the edges and features to acceptable levels.

## 2. SAR FILTERING CONSIDERATIONS

According to Lopes et al. (1990 b) common adaptive statistical filters have been developed based on the multiplicative noise model that assumes backscatter from a pixel originates from a large number of scatterers with independent phase and amplitude. This is not the case for built-up areas. Moreover, for the edges and some textured areas where details are smaller than the spatial resolution, the multiplicative noise model is unsatisfactory. Hence, for these two situations these filters are not efficient. On the other hand the filters mentioned above are based on using the local coefficient of variation, which is the ratio of standard deviation to the mean of pixels. This is known

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to be an efficient index of the homogeneity level of pixels over an image, but not a good textural measure as are second order statistical indicators such as the variance (Paudyal et al., 1995). In addition to these considerations there are some other shortcomings of filters using coefficient of variation as follows:

1- Using the coefficient of variation for the pixels that surround a point backscatterer is not reliable, because the coefficients of variation of these pixels are large, since their coefficient of variation is affected by the central pixels which are expected to be the point scatterers. This shortcoming causes these pixels to be inadequately filtered compared with the point scatterers. Therefore, applying a robust algorithm to deal with this problem is a demanding task.

2- Pixels with coefficients of variation near to $C_{max}$, the maximum coefficient of variation, are not filtered. Also pixels with coefficients of variation near to $C_u$, the averaged coefficient of variation over homogeneous areas, are averaged; although they are not classified as homogeneous areas, the averaging process will cause details to be lost.

3- For most statistical filters, averaging the pixels in heterogeneous areas with edges can lead to errors in filtered pixel values, because pixels with different noise models are combined in the averaging process.

## 3. METHODOLOGY

According to the previous section, in order to reduce or remove the above problems the following tasks are required; (i) A more robust criterion to discriminate different parts of image must be developed, not only based on homogeneity, but also according to textural features, (ii) The averaging of pixel values should be based on pixels whose speckle noise models are similar, and (iii) The development of an algorithm that deals with pixels which surround point scatterers or have homogeneity levels near to the maximum coefficient of variation. The method developed in this paper has been based on the determination of four thresholds from a standard deviation map derived within a 5 ×5 window. The method can be extended to larger windows.

### 3.1 Textural Criterion

In this study we have used edge detection masks to generate a new criterion for separating different textural areas in a SAR image. Considering a 5 × 5 window, it is possible to divide this window into nine 3×3 sub-windows corresponding to nine geographic directions. The mean value for each sub-window, which is called a sub-mean, is calculated and four 3×3 edge detection filters are separately scanned over the sub-means. Then, the results are summed and set to absolute values. This process results in 4 numbers whose standard deviations can provide textural information for different parts of a SAR image. The standard deviation map can be used as a textural criterion. The edge detection filters used are as follows:

$$\begin{bmatrix}-1 & 0 & 1\\-1 & 0 & 1\\-1 & 0 & 1\end{bmatrix},\begin{bmatrix}0 & 1 & 1\\-1 & 0 & 1\\-1 & -1 & 0\end{bmatrix},\begin{bmatrix}1 & 1 & 1\\0 & 0 & 0\\-1 & -1 & -1\end{bmatrix},\begin{bmatrix}1 & 1 & 0\\1 & 0 & -1\\0 & -1 & -1\end{bmatrix}$$

According to Lee and Pottier (2009), these filters are affected by speckle noise less than other filters such as the Sobel filter.

#### 3.1.1 Areas without Edges

Since no significant edges or textural features exist in a homogeneous area, except for some isolated pixels with very high or low values, it is possible to select the average value of the standard deviation map, $V_{NE}$, as the threshold. The areas with the standard deviation map values below the threshold contain no significant feature. Isolated points and their surrounding pixels will have relatively high standard deviation values compared to other pixels. In order to reduce the number of these pixels that may be filtered during the filtering process, we defined a second threshold, $V_{NE\text{-}max}$, which is the maximum value of the standard deviation map over the homogeneous area. Since using the maximum value results in some edges to be smoothed over edge areas, in order to reduce this problem, it is possible to select an area that has no point scatterers, where the standard deviations follow irregular curves, over edge areas. The average standard deviation of this area is the second threshold for the homogeneous area with a value between $V_{NE}$ and maximum value of standard deviations. In summary, the non-edged area is divided into two different sub classes using two thresholds.

#### 3.1.2 Edge Areas

The second class includes pixels that include edges and textural information. The low threshold of this class is $V_{NE\text{-}max}$ which is the high threshold of the previous class. The high threshold of this class, $V_{E\text{-}max}$ can be the maximum value in the standard deviation map over the area that includes edges and textural information. However, in order to decrease speckle noise level more over the heterogeneous area, it is better to select the average value of the standard deviation map over point scatterer areas as the high threshold for this class. The map of standard deviations over these areas appears as circular shapes, or closed curves.

#### 3.1.3 Isolated Point Targets

The third class covering the remainder of image represents the point scatterer pixels and their neighbours. These pixels appear as closed curves and circular shapes in the standard deviation map and have the highest values. Figure 1 shows a part of standard deviation map including the different classes.

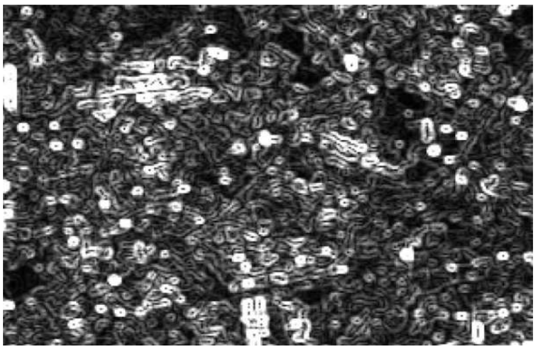

Figure 1. Standard deviation map for a part of study area; the brightest closed curves represent features, opened curves are edge areas and dark parts indicated homogeneous areas.

### 3.2 Filtering Scenarios

Since there are three different classes in terms of textural information over the images with different homogeneity levels, according to Lopes (1990 b) we need to use different scenarios for these different classes.

#### 3.2.1 Non-edge Class Filtering

According to previous section this class should be divided in two sub classes. The first sub class includes pixels with standard deviation values less than or equal to $V_{NE,}$ which means that there is no textural information over this sub class. Hence, a minimum variance unbiased estimator can efficiently reduce the speckle noise level over this sub class without considering the textural information. The second sub class that comprises pixels with standard deviation values between $V_{NE}$ and $V_{NE\text{-}max}$, describes isolated point scatterers. In this case there are two groups of pixels (i) pixels whose coefficients of variation are less than or equal to $C_{max}$ , the coefficient variation over heterogeneous area, and (ii) pixels with coefficients of variation higher than $C_{max}$.

For the first 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 group represents isolated points and their surrounding pixels. According to section 2, one of the most important problems with the existing filters is that they consider the neighbouring pixels of point scatterers in the same way as the point scatterers themselves, since the coefficient of variation is not reliable 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 we developed an algorithm that is called 'point scatterer discriminator'. This algorithm is based on the assumption that the difference of pixel values between point scatterers and their neighbours is high. 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 the following equation is executed on all pixels within the window:

$$D = \frac{DN_{max} - DN_{ij}}{DN_{max} - DN_{min}} \qquad (1)$$

Where $DN_{max}$= the highest value within selected window

$DN_{min}$= the lowest value within selected window

$DN_{ij}$= the pixel value of pixel (i,j)

Then the median and mean values for the matrix of the differences, D, 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, otherwise the pixels whose difference values are more than or equal to M are selected and the coefficient of variation for selected pixels is calculated. As mentioned this sub class is not expected to include textural information except point scatterers. For this reason, the pixel is known as a point scatterer provided its coefficient of variation is higher than $C_u$, the averaged coefficient of variation over a homogeneous area, otherwise the mean value of the selected pixels is assigned as a filtered pixel value. Some isolated points with very low pixel values derived from this algorithm may also be preserved. These points are not recognized as point scatterers in the first step of this algorithm; however, the second and third steps can solve this problem.

### 3.2.2 Edge Class Filtering

Filtering the image over this class is more complicated than the other classes because these areas include textural information such as edges and built-up areas. For this reason, using the mean value over this class causes smoothing of the textural information and degrading of the image details; however, there will still be some homogeneous areas within this class that should be smoothed using a mean filter. Since the mean value of the standard deviation map over the point scatterer areas is used for $V_{E\text{-}max}$, there will be some point scatterers over this class that should be preserved. According to these considerations there are three types of pixels, those for which C is less than or equal to $C_u$, those for which C is between $C_u$ and $C_{max}$ and those whose coefficients of variation are more than $C_{max}$.

According to Lopes et al. (1990 b), pixels whose coefficients of variation are less than or equal to $C_u$ follow a fully developed speckle noise model, and should be averaged. Since within the edge classes the pixel values vary in terms of homogeneity level, averaging all pixels should result in a loss of detail. So, it is necessary to select only pixels whose coefficients of variation are less than or equal to $C_u$ for averaging. For the pixels whose coefficients of variation are higher than $C_{max}$, the point scatterer discriminator algorithm is used, thus preserving the point scatterers and their neighbours.

The most complicated filtering in this class is on the pixels whose coefficients of variation are between $C_u$ and $C_{max}$ because pixels in this category display edges and more textured areas. On one hand using simple averaging for these pixels is unreliable because of the high variability among the pixels. On the other hand, even if we utilize averaging using only pixels whose coefficients of variation are between $C_u$ and $C_{max}$, it will introduce errors because they are not the result of fully developed speckle model. Hence, weighted averaging using more similar pixels in terms of homogeneity is more reliable for the filtering.

In order to deal with filtering of this part, after selecting pixels whose coefficients of variation are between $C_u$ and $C_{max}$, the following equation called homogeneity likelihood (HL) is applied to find pixels of similar homogeneity within a window with respect to the central pixel:

$$HL = \left| \frac{C_c - C_{ij}}{C_{max} - C_u} \right| \qquad (2)$$

Where $C_c$= coefficient of variation for central pixel

$C_{ij}$= coefficient of variation for pixel (i,j) within the window

This index shows the similarity between neighbouring pixels with no fully developed speckle model and the central pixel. 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:

$$\begin{cases} w_{ij} = \exp(-HL) & \text{if } C_u < C_{ij} < C_{max} \\ w_{ij} = \exp(-\infty) & \text{if } C_{ij} <= C_u \text{ or } C_{max} <= C_{ij} \end{cases} \qquad (3)$$

And in order to normalize the weighting factors, we have:

$$W = \sum_i^m \sum_j^n w_{i,j} \qquad (4)$$

Then the weighted mean value is calculated as follows:

$$\bar{Z}_w = \frac{\sum_i^m \sum_j^n w.Z_{i,j}}{W} \qquad (5)$$

Where $Z_{i,j}$ is the pixel value (i,j)

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

$$\text{Filtered pixel} = \bar{Z}_w \times B + Z \times (1-B) \qquad (6)$$

B is calculated according to the following equation:

$$B = \exp(-K \times N) \qquad (7)$$

Where K = damping factor

And N is calculated as follows:

$$N = \frac{C_{Sij} - C_u}{C_{max} - C_{Sij}} \qquad (8)$$

Where $C_{Sij}$ = coefficient of variation for selected pixels

It is apparent that equations (6), (7) and (8) are similar to the equations that were proposed for enhanced Lee filter. It means that the more heterogeneous the pixels, the less filtering. However, there are some differences with the enhanced Lee filter including using the weighted mean instead of simple averaging, and applying the coefficient of variation for the selected pixels instead of calculating this value for all pixels within the window. There are some advantages in applying these changes. First, as mentioned in section 2, pixels whose coefficients of variation are close to $C_u$ are averaged; however, their coefficients of variation are higher than $C_u$ and their speckle model is not fully developed. Through using the weighted mean, this problem is removed because if B equals 1, then the filtered value is set to the weighted mean based on the noise model similarity. Moreover, for the pixels whose coefficients of variation are close to $C_{max}$ the Enhanced Lee filter treats them as point scatterers, while the modified method is able to filter them through calculating the coefficient of variation for the selected pixels.

### 3.2.3 Point Scatterer Class Filtering

Pixels that have values more than or equal to $V_{E\text{-}max}$ in the standard deviation map are categorized as point scatterer candidates because some of them are pixels surrounding point scatterers. Therefore, it is necessary to use the point scatterer discriminator algorithm to find which pixels are point scatterers.

## 4. FILTER ASSESSMENT

There are several methods to assess the filtered image quantitatively according to different aspects such as noise reduction, edge preservation, feature preservation (Sheng and Xia, 1996). The results of these different measurements can be contradictory. Hence, different assessment methods should be used to find the optimum tradeoff among the different aspects of image quality assessment (Qui et al., 2004).

### 4.1 Equivalent Number of Looks (ENL)

This index is calculated using the following equation (Gagnon and Jouan, 1997):

$$ENL = \left(\frac{mean}{standard\ deviation}\right)^2 \qquad (9)$$

The higher ENL value for a filter, the higher efficiency in smoothing speckle noise over homogeneous areas.

### 4.2 Speckle Suppression Index (SSI)

This index is based on the equation as follows:

$$SSI = \frac{\sqrt{var(I_f)}}{mean(I_f)} \times \frac{mean(I_o)}{\sqrt{var(I_o)}} \qquad (10)$$

Where $I_f$ = filtered image

$I_o$ = noisy image

This index tends to be less than 1 if the filter performance is efficient in reducing the speckle noise (Sheng and Xia, 1996).

### 4.3 Speckle Suppression and Mean Preservation Index (SMPI)

ENL and SSI are not reliable when the filter overestimates the mean value. We developed an index called Speckle Suppression and Mean Preservation Index (SMPI). The equation of this index is as follow:

$$SMPI = Q \times \frac{\sqrt{var(I_f)}}{\sqrt{var(I_o)}} \qquad (11)$$

And Q is calculated as follows:

$$Q = R + |mean(I_o) - mean(I_f)| \qquad (12)$$

$$\text{Where} \quad R = \frac{\text{Max}(\text{mean}(I_f)) - \text{Min}(\text{mean}(I_f))}{mean(I_o)} \qquad (13)$$

According to this index, lower values indicate better performance of the filter in terms of mean preservation and noise reduction.

### 4.4 Edge-Enhancing Index (EEI)

This value indicates how much a filter is able to preserve the edge areas and is defined as (Sheng and Xia, 1996):

$$EEI = \frac{\sum|DN_{1f} - DN_{2f}|}{\sum|DN_{1o} - DN_{2o}|} \qquad (14)$$

Where, $DN_{1f}$ and $DN_{2f}$ = filtered values of the pixels on either side of the edge

$DN_{1o}$ and $DN_{2o}$ = original values of the corresponding pixels

EEI values are usually less than 1 and higher values indicate better edge preservation capability.

### 4.5 Image Detail-Preservation Coefficient (IDPC)

The correlation coefficient between original image and filtered image over fine details such as point scatterers is defined as IDPC (Sheng and Xia, 1996).

## 5. RESULTS

In order to test the Proposed algorithm, we used ground-range HH and HV polarized L-band magnitude ALOS data that were extracted from SLC data with dimensions 2031×1936 pixels. These images cover some homogeneous areas such as water bodies, forests, agricultural lands and urban areas and HH polarized image is shown in figure 2.

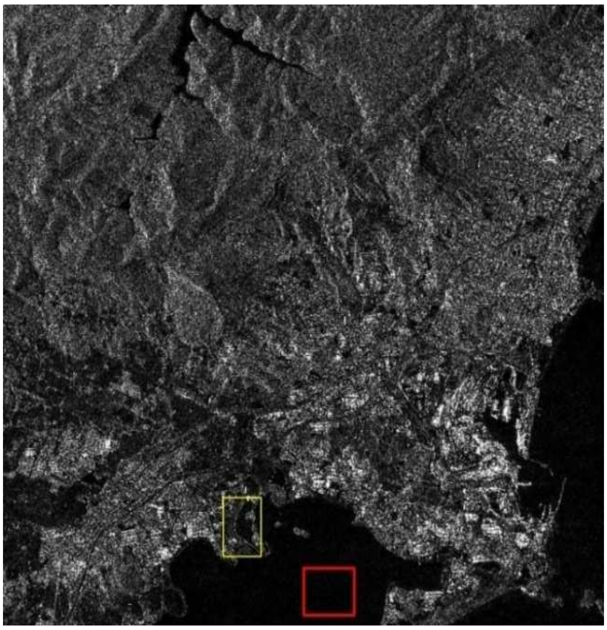

Figure 2. The HH polarized L band image; red rectangular shows the selected homogeneous area, yellow rectangular represents the selected edged area

### 5.1 Speckle Reduction

For the assessment of the performance of the filters to suppress speckle noise over selected homogeneous area, we used the three indices shown in table 3.

| Filter | image | Mean ($\times10^{-3}$) | SD ($\times10^{-3}$) | ENL | SSI ($\times10^{-3}$) | SMPI ($\times10^{-3}$) |
|---|---|---|---|---|---|---|
| Noisy image | HH | 101.30 | 53.3 | ---- | ---- | ---- |
| | HV | 28.70 | 14.8 | ---- | ---- | ---- |
| Lee | HH | 101.31 | 16.8 | 36.37 | 315 | 8.2 |
| | HV | 28.70 | 4.3 | 44.55 | 291 | 7.5 |
| Kuan | HH | 101.31 | 16.8 | 36.37 | 315 | 8.2 |
| | HV | 28.70 | 4.4 | 42.55 | 297 | 7.7 |
| MMSE | HH | 101.31 | 16.8 | 36.37 | 315 | 8.2 |
| | HV | 28.70 | 4.3 | 44.55 | 291 | 7.5 |
| Frost K=1 | HH | 101.30 | 18.1 | 31.32 | 340 | 8.8 |
| | HV | 28.70 | 4.7 | 37.29 | 318 | 8.2 |
| Enhanced Lee K=1 | HH | 100.95 | 28.5 | 12.55 | 537 | 16.8 |
| | HV | 28.60 | 8.2 | 12.16 | 556 | 16.2 |
| Gamma Map | HH | 98.70 | 20.9 | 22.30 | 402 | 20.2 |
| | HV | 27.96 | 5.76 | 23.56 | 399 | 20.1 |
| Proposed K=1 | HH | 101.16 | 18.9 | 28.65 | 355 | 9.6 |
| | HV | 28.70 | 5.1 | 31.67 | 345 | 8.9 |

Table 3. Speckle noise reduction indices for the filtered images

As table 3 shows, the performance of Lee, Kuan and MMSE filters are very good for suppressing the speckle noise over the homogeneous areas whereas Enhanced Lee filter is not able to reduce the speckle noise efficiently. The Proposed method listed in the last line of table 3 shows comparable results in speckle noise reduction for HH polarized image.

### 5.2 Edge Preservation

In order to use EEI index, the edge between water body and land was selected. This area is shown within a yellow rectangle in figure 1. The results of this index for the filters are given in table 4. The best algorithm performance for the edge preservation with the highest EEI values is the Enhanced Lee and the Proposed method respectively. On the other hand, Frost, Kuan, Lee and MMSE filters are not able to preserve the edges. It is estimated that in filtered images derived using the Enhanced Lee filter and the Proposed method, edges are up to 2 times sharper than Lee, Kuan, MMSE and frost filters.

| Filter | image | EEI ($\times10^{-3}$) |
|---|---|---|
| Lee | HH | 396.7 |
| | HV | 262.8 |
| Kuan | HH | 448.1 |
| | HV | 289.5 |
| MMSE | HH | 361.9 |
| | HV | 244.5 |
| Frost K=1 | HH | 313.4 |
| | HV | 254.8 |
| Enhanced Lee K=1 | HH | 999.7 |
| | HV | 918.1 |
| Gamma Map | HH | 968.2 |
| | HV | 731.6 |
| Proposed K=1 | HH | 999.0 |
| | HV | 833.2 |

Table 4. Edge index values for different filters

### 5.3 Preservation of Details

More than one thousands pixels representing significant features were selected separately over the two images and, the correlation between filtered and original images over the selected pixels was calculated. Table 5 presents the results of this index. The best feature preservation performance belongs to Proposed method and Enhanced Lee filter for which their index values show no variation for all features.

| Filter | image | IDPC |
|---|---|---|
| Lee | HH | 0.94 |
| | HV | 0.96 |
| Kuan | HH | 0.95 |
| | HV | 0.96 |
| MMSE | HH | 0.94 |
| | HV | 0.94 |
| Frost K=1 | HH | 0.91 |
| | HV | 0.89 |
| Enhanced Lee K=1 | HH | 1.00 |
| | HV | 0.99 |
| Gamma Map | HH | 0.98 |
| | HV | 0.98 |
| Proposed K=1 | HH | 1.00 |
| | HV | 1.00 |

Table 5. IDCP of the filters over selected features

### 5.4 Filtering of Pixels

According to section 2, some pixels should be preserved and do not need to be filtered. On the other hand, a filtering method should filter all pixels where necessary. As mentioned earlier, some pixels surrounding features and point scatterers that should be filtered but are not filtered by the Enhanced Lee and Gamma filters because of the deficiency of the coefficient of variation in their location. We developed an algorithm to deal with this problem. In order to assess this algorithm, 100 pixels representing point scatterers were selected over these images and the coefficient of variation map assessed. Then the filtered pixels were divided by the corresponding pixels of original images within a 5×5 window. In this way, pixels whose values are 1 are categorized as unfiltered pixels. The results were given in table 6.

| Filter | Image | Number of unfiltered pixels | Filtering performance (%) |
|---|---|---|---|
| Enhanced Lee K=1 | HH | 2229 | 11 |
| | HV | 2347 | 6.1 |
| Gamma Map | HH | 2162 | 13.5 |
| | HV | 2322 | 7.1 |
| Proposed K=1 | HH | 1374 | 45 |
| | HV | 1459 | 41.6 |

Table 6. Number of unfiltered pixels over point scatterers

Table 6 reveals that the point scatterer discriminator algorithm can perform very effectively in compensating for the deficiency of calculating the coefficient of variation for the pixels which are near the point scatterers. As this table shows, filtering performance for the Enhanced Lee and Gamma filters over selected point scatterer areas are very poor as they are able to filter less than 14 percent of these pixels whereas the proposed filter increases the number of filtered pixel to 45 percent.

## 6. CONCLUSION

In this study a new algorithm based on coefficient of variation similarity and using a new criterion to segment different parts of the SAR image has been proposed. This method was compared to six common filters using different quantitative assessment methods. According to the assessments that were used in this study, some filters such as Lee, Kuan and MMSE filter perform very efficiently in dealing with the problem of speckle noise at the expense of smoothing features and edges. Some other filters such as Enhanced Lee and Gamma Map can preserve details very efficient, but they are not able to reduce speckle noise. In addition to this, the inadequacy of the coefficient of variation causes these filters to be unable to deal with the problem of speckle noise of the pixels surrounding point scatterers and fine features. Meanwhile, pixels whose coefficients of variation are close to $C_u$ are averaged, while if they are higher than $C_u$ they should be treated as pixels whose speckle noise model is not fully developed.

In this study we proposed a novel model to deal with these problems. As the results show, the proposed filtering method can perform acceptably well in speckle reduction and simultaneously edge and feature preservation. In addition to this, the point scatterer discriminator algorithm that was developed in this study and used in the structure of the proposed method can compensate for the deficiency in the coefficient of variation in separating between point scatterers or features and the pixels surrounding them. Finally, the proposed method is being examined to prove its validity for other types of data.

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