Despeckling of SAR Imagery Using Contourlet Transform in A Homomorphic Framework

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ABSTRACT

In this paper, a homomorphic framework is used for the enhancement and retrieval of speckled image. The log function at the starting of the structure is used to transform the speckled image (with multiplication noise) to a noisy image (with additive noise). This image is then applied to classical contourlet transform to decompose the noisy image into approximation and details. To retrieve the image without speckle noise, some suitable threshold level is chosen. In the reconstruction part, inverse contourlet transform is performed with an exponential function to compensate for the log one. The proposed technique is compared with other techniques. The result of comparison reflects the proposed technique superiority.

Keywords: De-speckling, SAR images, Contourlet transform, Homomorphic framwork.

إزالة الضوضاء الرقطية من صور SAR باستخدام التحويل الكنتوري في البناء المتماثل

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الملخص

في هذا البحث تم إستخدام تقنية البناء المتماثل وهي مفيدة لتحسين وإسترجاع الصور المصابة بضوضاء الرقط (Speckles). العملية تتم بإدخال الصورة على الدالة اللوغارتمية لتحويلها من صورة مصابة بالضوضاء الرقطية (اي بضوضاء ضربية) إلى صورة مصابة بالضوضاء الجمعية ومن ثم إدخالها إلى تحويل الكونتورلت التقليدي لتجزئتها الى جزء مقارب وتفاصيل. ولإسترجاع الإشارة بدون ضوضاء رقطية يتم إختيار حد عتبة مناسب.وفي مرحلة التركيب يتم استرجاع الصورة باستخدام تحويل الكونتورلت المعكوس مع دالة أسيّة لإلغاء تأثير الدالة اللوغارتمية على الصورة. لقد تم مقارنة الطريقة المقترحة مع عدة طرائق أخرى وعكست النتائج جدارة الطريقة المقترحة.

الكلمات المفتاحية: إزالة الضوضاء الرقطية، صور SAR ، التحويل الكنتوري، البناء المتماثل.

1. Introduction

The main feature of contourlet transforms (CTs) is the potential to efficiently handle 2-D singularities, *i.e.* edges, unlike wavelets which can deal with point singularities exclusively [4]. This observation is due to the fact that wavelets are blind to the smoothness along the edges commonly found in images [12]. The drawback for wavelets in 2-D is their limited ability in capturing directional information. To counter this deficiency, researchers have most recently shifted their attention to multiscale and directional representations that can capture the intrinsic geometrical structures such as smooth directional contours in natural images. Some examples include the steerable pyramid, brushlets, complex wavelets, and the curvelet transform. Contourlets not only possess the main features of wavelets (namely, multiresolution and time frequency localization), but also show a high degree of directionality and anisotropy. Contourlets allow for a different and flexible number of directions at each scale, while achieving nearly critical sampling. In addition, contourlet transform employs iterated filter banks, which makes it computationally efficient [5]. The original construction of the curvelet transform was intended for functions defined in the *continuum* space R^2. The development of *discrete* versions of the curvelet transform that can be applied to sampled images is a challenge, especially when critical sampling is desirable [10].

The contourlet transform is thus developed as a true two-dimensional representation that can capture the geometrical structure in pictorial information. Unlike other transforms that were initially constructed in the continuous-domain and then discretized for sampled data, the contourlet construction starts from the discrete-domain using filter banks, and then convergences to a continuous-domain expansion via a multiresolution analysis framework [11]. It consists of two major stages: the subband decomposition and the directional transform. At the first stage, Laplacian pyramid (LP) is used, and for the second one directional filter banks (DFB) is applied [12].

Contourlet-based denoising methods have shown great potential and are very competitive with wavelet-based denoising methods [3]. Speckle, a form of multiplicative, locally correlated noise, plagues imaging applications such as in medical ultrasound image and synthetic aperture radar (SAR) images. For images that contain speckle, a goal of enhancement is to remove the speckle without destroying important image features [16]. Many adaptive filters for SAR image denoising have been proposed in the past.

A SAR image is affected by speckle in its acquisition and processing. Image de-speckling is used to remove the multiplicative speckle while retaining as much as possible the important signal features. In recent years there has been an important amount of research on wavelet thresholding and threshold selection for SAR despeckling because wavelet provides an appropriate basis for separating noisy signal from the image signal [6] [7]. In this paper, a homomorphic contourlet despeckling technique is proposed. The technique combines two non linear transformations; the homomorphic framework and the CT thresholding. The homomorphic nonlinear processing is based on replacing each pixel value of the speckled image by its log-transformation then contourlet thresholding is applied for further nonlinear transform domain processing. An exponential operation on the filtered output is used to simulate the final homomorphic antilog-transformation stage and to obtain the despeckled image. The homomorphic transformation is presented in section 2. The CT transform is described in section 3. Section 4 contains speckle model with homomorphic filtering. The proposed technique is presented in section 5. Results are contained in section 6. Finally, section 7 concludes this paper.

2. Homomorphic Trasformation

Homomorphic transformation can sometimes be a reasonable way of converting signal-dependent or pure multiplicative noise to an additive noise, which then can be filtered appropriately. The homomorphic approach is initially introduced by Jain [2], where a speckled image is first log-transformed to make the multiplicative speckle noise additive. The log-transformed image is then subjected to a filter, followed by an exponential operation on the filtered output to obtain the despeckled image (see Fig.1). However, this method essentially, being a filter blurs many important signal features. More recently, there has been much research on many new contourlet techniques for speckle reduction in SAR images. A homomorphic framework can provide a better reduction of the speckle noise. Theoretically, it is known that the multiplicative noise is the ratio of the standard deviation to the signal mean value. Such ratio is usually treated as a constant at every pixel in the SAR image. Based on this assumption, which is not the case in practice, most of the filters for speckle reduction are designed [15].

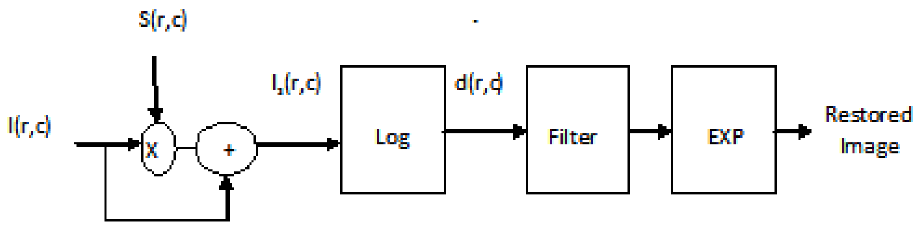


Fig. 1 A signal flow diagram of a typical homomorphic transformation.

3. Contourlet Transformation

The contourlet transform consists of two major stages: the subband decomposition and the directional transform. At the first stage, Laplace Pyramid (LP) is used to decompose the image into subbands, and then the second one is a Directional Filter Bank **(**DFB) which is used to analyze each detail image. A flow graph of the CT is shown in Fig. 2.

The contourlet transform was proposed as a directional multiresolution image representation that can efficiently capture and represent singularities along smooth object boundaries in natural images. Its efficient filter bank construction as well as low redundancy make it an attractive computational framework for various image processing applications. However, a major drawback of the original contourlet construction is that its basis images are not localized in the frequency domain [15].

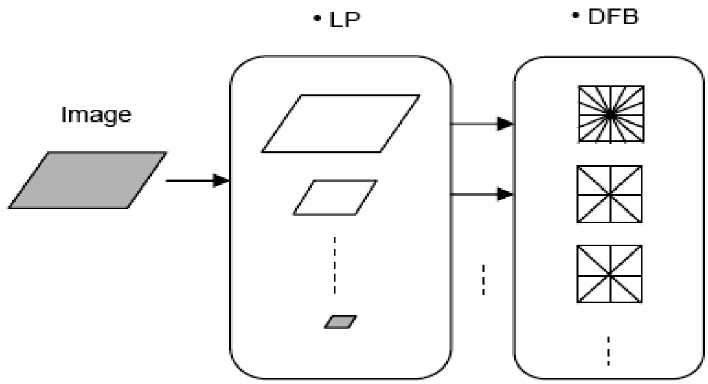


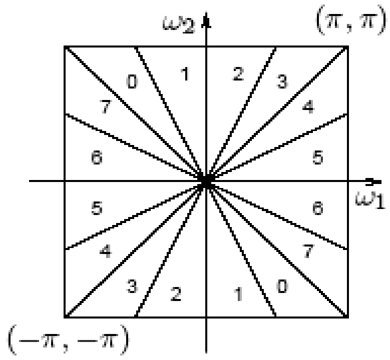
Fig. 2 A flow graph of the contourlet transform. Image is first decomposed into subbands by LP and then each detail image is analyzed by DFB.

3.1 Laplace pyramid

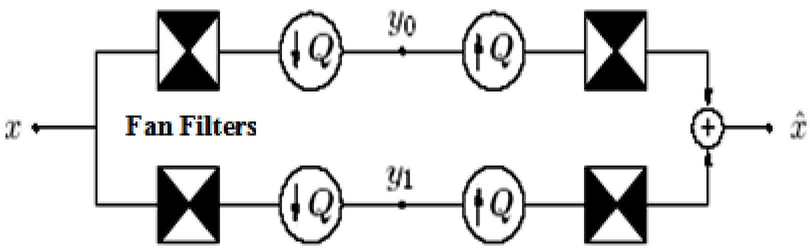
The Laplace filters in the transform toolbar for images detect rapid changes in pixels using two different analytic matrices. The Laplace filters often result in "negative" images with brighter tones at detected features and dark or black tones elsewhere. These filters will emphasize linear features such as edges. In the first stage of the decomposition, the original image is transformed into a coarse signal and a detail signal. The coarse signal has fewer samples than the original image but the detail signal has the same number of samples as the original image. The coarse signal is a filtered and down sampled version of the original image. It is then up sampled and filtered to predict the original image. The prediction residual constitutes the detail signal. The coarse signal can be decomposed, further and this process can be repeated a few times iteratively. This yields a pyramid consisting of the coarsest version thus obtained and the detail signals at various scales. This pyramid is called Laplace pyramid [1].

3.2 The directional filter banks

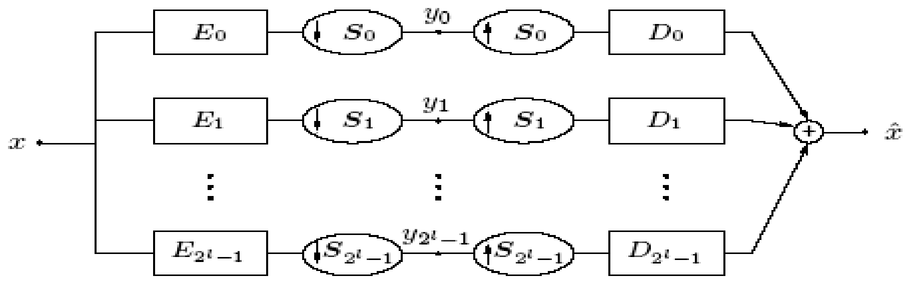
Directional Filter Bank (DFB) is designed to capture the high frequency (representing directionality) of the processing image. Bamberger and Smith constructed a two-dimensional (2-D) DFB that can be maximally decimated while achieving perfect reconstruction. A new construction for the DFB to avoid modulating input image is proposed, by which we can obtain the desired 2-D spectrum division as shown in Fig. 3(a). The simplified DFB is intuitively constructed from two building blocks. The first is a 2-D spectrum into two directions: horizontal and vertical, as shown in Fig. 3(b). The second is a shearing operator, which is used to reordering the image samples. By appropriate combination of shearing operators together with two-direction partition of quincunx filter banks at each node in a binary tree-structured filter bank, shown in Fig. 3(c) [13], the CT structure is obtained.



(a) Frequency partitioning.



(b) 2-D spectrum partition using quincunx filter banks with fan filters.



(c) The multichannel view of a one level tree-structured DFB, E_i's, (i= 0,1,2,.. 2^{l-1}), are the analysis filter functions, D_i's, (i= 0,1,2,.. 2^{l-1}), are the synthesis filter functions, and S_i's, (i= 0,1,2,.. 2^{l-1}), are either the down- or up- samplers.

Fig. 3 The directional filter bank.

4. Speckle Model With Homomorphic Filtring

Speckle noise in SAR images is usually modeled as multiplicative noise process of the form

$I_s(r,c)=I(r,c) + I(r,c).S(r,c)$

$= I(r,c).[\ 1 + S(r,c)]$ …(1)

or $I_s= I(r,c) * N_s(r,c)$ …(2a)

where

$N_s(r,c)=1+S(r,c)$ …(2b)

The true radiometric values of the image are represented by $I(r,c)$, and the values measured by the radar instrument are represented by $I_s(r,c)$. The speckle noise is represented by $S(r,c)$. The parameters r and c mean row and column of the respective pixel of the image. For single-look SAR images, S(r,c) is Rayleigh distributed (for amplitude images) or negative exponentially distributed (for intensity images) with a mean of 1. For multi-look SAR images with independent looks, S has a gamma distribution with a mean of 1 [6], [7].

Homomorphic filters are widely used in image processing for compensating the effect of nonuniform illumination in an image. Pixel intensities in an image represent the light reflected from the corresponding points in the objects. Homomorphic filtering is a generalized technique for image enhancement and restoration. It simultaneously normalizes the brightness across an image and increases contrast. Most importantly, homomorphic filters transform multiplicative noise into additive noise using the logarithmic operator [6].

Applying homomorphic transformation, the log-transform of eq. (*2a*) yields an additive speckle model of the type given by

$$d(r,c) = f(r,c) + N(r,c) \quad \ldots(3)$$

where $d(r,c) = Log\{I_s(r,c)\}$, …(4a)

$f(r,c) = Log\{I(r,c)\}$, …(4b)

and $N(r,c) = Log\{N_s(r,c)\}$ …(4c)

Since the original image detected pixel values can be factorized into two components as follows:

$$I(r,c) = L(r,c) \times R(r,c) \quad \ldots(5)$$

where $L(r,c)$ is the luminance and $R(r,c)$ is the reflectance of the scene, then eq. (*5*) can be rewritten as

$$f(r,c) = LL(r,c) + LR(r,c) \quad \ldots(6)$$

where $LL(r,c) = Log\{L(r,c)\}$ …(7a)

and $LR(r,c) = Log\{R(r,c)\}$ …(7b)

Thus, eq. (*6*) can then be rewritten as

$$d(r,c) = LL(r,c) + LR(r,c) + N(r,c) \quad \ldots(8)$$

which means that each log-transformed pixel in the speckled image $d(r,c)$ consists three additive components; A low frequency one $LL(r,c)$ and two high frequency components $LR(r,c)$ and $N(r,c)$. On the log-transformed speckled image pixel $d(r,c)$, the filter in Fig. 1 can isolate the high frequency noise component $N(r,c)$, but it will also blur many important signal features due to elimination of high frequency image pixel component $LR(r,c)$ [7], [9].

5. The Proposed Technique

An alternative way is to use contourlet thresholding in a homomorphic framework. In such a frame, the log-transformed image $d(r,c)$ is applied to a 2-D discrete contourlet transform (DCT). Many modified contourlet-based and homomorphic contourlet-based despeckling techniques are designed as in most of those techniques suffer from high computational complexity drawbacks. In this section, a new homomorphic contourlet-based despeckling technique is proposed in a homomorphic framework. contourlet thresholding The filtering stage in Fig.1 is replaced by a 2-D DCT, thresholds on the details and a 2-D IDCT as shown in Fig. 4(a). By such replacement, the linear filtering process is changed to a nonlinear one by thresholding the DCT detail coefficients, in addition to the preliminary nonlinear operation of the log-transformation as a starting stage in the original homomorphic framework of Fig. 1. One of advantages of the proposed technique is that the two nonlinear processes in the technique are useful in the reduction of the nonlinear (multiplicative) noise, such as speckles. The method to reduce noise (with detail preservation) by speckle filtering have also benefited from the use of redundant multiscale representations of the LP part [13]. Another advantage is that it utilizes the tree-structure realization for the DBF part of the DCT in both analysis and synthesis banks. This realization makes the whole structure suitable for VLSI implementation, since it possesses some modularity and regularity in its realization, especially, with the use of lattice all-pass sections $A_0(z_1,z_2)$, $A_1(z_1,z_2)$, $B_0(z_1,z_2)$ and $B_1(z_1,z_2)$ as shown in Figs. 4(b) and 4(c).

6. Results

6.1 Assessment parameters

The assessment parameters that are used to evaluate the performance of speckle reduction are as follows:

A) *Peak signal to noise ratio (PSNR)*:

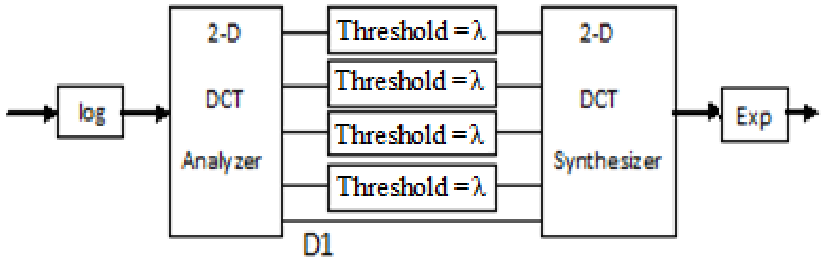
A method may be the more accurate one to measure image quality and speckle removal efficiency. It is used to evaluate the difference between two images. It is defined as:

$$PSNR = 20 \times Log\left(\frac{b}{rms}\right) \qquad \ldots(9)$$

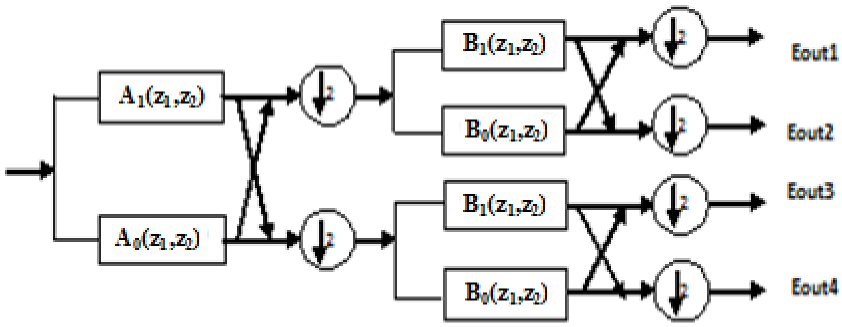
where

$$rms = \sqrt{\frac{\sum_{r,c}\left[F(r,c) - \hat{F}(r,c)\right]^2}{R \times C}} \qquad \ldots(10)$$

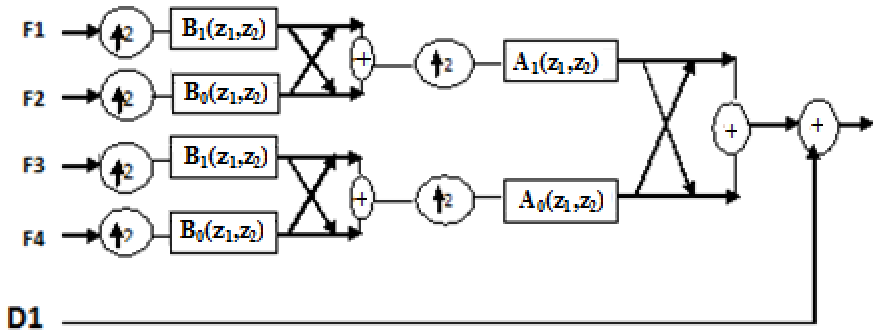
b is the largest possible value of the signal (typically 255 for 8-bit pixels), and rms is the root mean square difference between two images. The two images are the original image F(r,c) and the reconstructed image $\hat{F}(r,c)$. The *PSNR* is given in decibel units (dB), which measure the ratio of the peak signal and the difference between two images. An increase of 20 dB corresponds to a ten-fold decrease in the *rms* difference between two images [6], *R-by-C* pixels is the size of the despeckled image.



(a) The proposed block diagram.



(b) 4-band (DBF) of the contourlet transformation analysis bank.



(C) CT reconstruction

Fig. 4 The proposed despeckling technique.

B) *Noise Mean Value (NMV), Noise Variance (NV), and Noise Standard Deviation (NSD)*: *NV* determines the contents of the speckle in the image. A lower variance gives a "cleaner" image as more speckle is reduced, although, it not necessarily depends on the intensity. The formulas for the *NMV*, *NV* and *NSD* calculation are

$$NV = \frac{\sum_{r,c}\left[\hat{F}(r,c) - NMV\right]^2}{R \times C} \quad \ldots(11)$$

$$NMV = \frac{\sum_{r,c}\hat{F}(r,c)}{R \times C} \quad \ldots(12)$$

$$NSD = \sqrt{NV} \quad \ldots(13)$$

The estimated noise variance is used to determine the amount of smoothing needed for each type of filter [8].

6.2 A comparative study

The proposed technique is tested in this section by despecling two images. A 256 x 256 E-SAR image (original noisy image 1) of Oberpfaffenhofen, Germany (L-band, 1.5m x 1.5m) provided by the DLR (see Fig. 5). The image has been resampled in azimuth and decimated by a factor 2 (the resampling process leads to an effective number of looks equals to 2 looks). Many threshold levels are tested and the one which gives best performance restored image is chosen. The resulting restored image by the proposed technique is compared with three restored images from recent techniques namely; SWT-MMSE, SWT-Soft and Curv-Soft [14]. The resulting images of those techniques with the proposed one are shown in Fig. 5, while Table-1 illestrates the assessment parameters for all resulting restored images. ERS SAR Precision Image (PRI) standard of Buenos Aires area is used as an original noisy image 2 (see Fig. 6). Such image is from remote sensing satellite ERS-2 with 242 x 242 pixels. The de-speckled images, processed by using recent techniques, including the proposed one are also shown in Fig. 6. For best performance of the proposed technique, threshold levels of λ= 0.01 is chosen for image 1 and of 0.0123 for image 2. From Figs. 5 and 6, it can be seen that the proposed technique is a successful tool for eliminating speckle without distorting any useful image information, *i.e.,* keeping important image edges preserved.

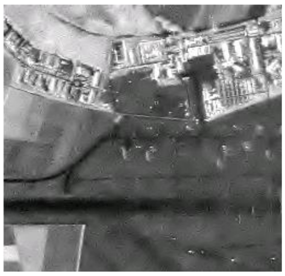
Table 1 also illustrates the objective assessment parameters for different images shown in Fig. 6. The quantitative results of Table 1 again highlight the ability of the proposed technique to eliminate speckle, preserving the useful image information, since it gives good *PSNR* values (37.31 db for image1 and 41.01 db for image 2) with best variance reductions (*NSD* = 26.64 for image 1 and 26.27 for image 2). It can be seen that, the proposed technique provids better reductions in speckle noise as compared with other recent techniques.

7. Conclusions

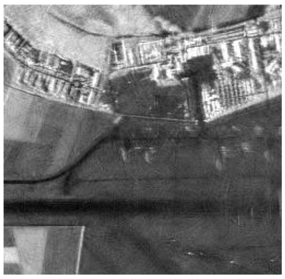
A despecckling technique has been proposed, based on the use of a homomorphic framework with a stage of a filter being replaced by the contourlet thresholding. The despeckled images from such method possess good qualities as shown in Figs. 5 and 6 with best *PSNR* and minimum *NSD* values as illustrated Table 1. It should be noted that because the mean of log-transformed speckle noise does not equal to zero, thus a d.c correction is required to avoid extra distortion in the restored image. It should also be noted that the proposed technique is accomplished with acceptable computational complexity.

(a) Original image 1.

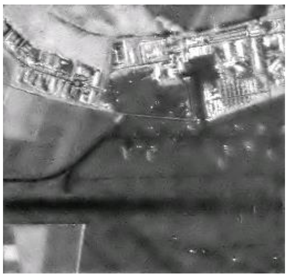
(b) SWT-MMSE.



(c) SWT-Soft.

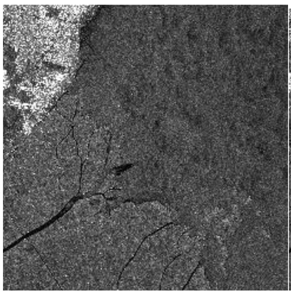
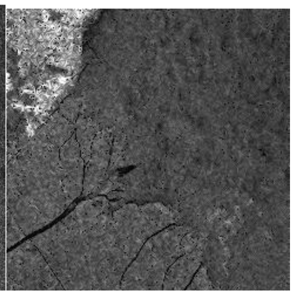


(d) Curv-Soft.

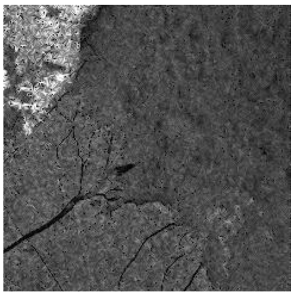
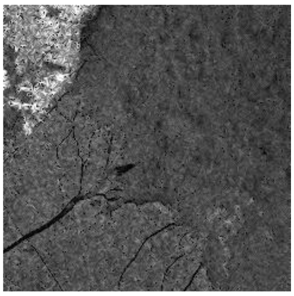


(e) The proposed.

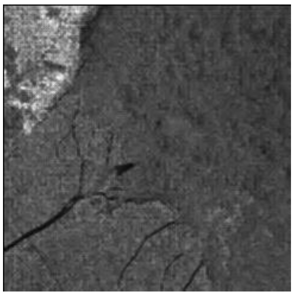
Fig. 5 The original image 1 and its corresponding resulting images for different techniques.

(a) Original image 2. **(b) SWT-MMSE.**

(c) SWT-Soft. **(d) Curv-Soft.**



(e) The proposed.

Fig. 6 The original image 2 and its corresponding resulting images for different techniques.

Table-1 :Assessment parameters of the resulting images for different techniques.

	Image 1		Image 2	
Technique	*PSNR* (db)	*NSD*	*PSNR* (db)	*NSD*
SWT-MMSE	34.55	46.61	38.96	35.82
SWT-Soft	35.23	42.26	39.06	33.31
Curv-Soft	36.02	36.76	39.15	32.89
The proposed	37.31	26.64	41.01	26.27

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