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Towards Deriving an Optimal Approach for Denoising of RISAT-1 SAR Data Using Wavelet Transform

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***Abstract*—Synthetic Aperture Radar(SAR) image filtering has been of interest since its inception. A variety of denoising filters for SAR images have been proposed in the recent years, which are targeted at removing the speckle noise to increase the contrast of the image, and make it useful for further image interpretation and applications. Of late, Wavelet based SAR data denoising techniques have been gaining popularity due to its space-frequency localization capability and the capacity to analyse the data at different scales. In this paper, we have attempted to derive an optimal approach for wavelet based SAR image filtering based on the quality criteria which takes into account not only the radiometric quality but also the geometric quality using point target data of actual Corner Reflector. Different orders of Daubechies wavelet coefficients have been used in the DWT(Discrete Wavelet Transform) based approach. In this study all aspects of an image quality have been taken into consideration such as the geometric fidelity and the radiometric quality, and using a simple heuristic soft thresholding criteria, optimal basis has been arrived at.**

***Keywords:* SAR, speckle, denoising, Wavelet based denoising, thresholding, decomposition, mother wavelets, radiometric resolution, geometric resolution, corner reflector.**

I. Introduction

Synthetic Aperture Radar (SAR) imaging has become a popular means of acquiring remote sensing data by Earth Observation Satellite(EOS) sensors all across the world due to its all weather and day and night capability. The basic geometry of SAR and its active mode of signal acquisition entails a very complicated sensor design, signal processing, image processing and its interpretation [1-3]. The fundamental theory behind SAR needs transmission and reception of linearly frequency modulated chirp signals, and Doppler processing of the encoded returned echo[1][4]. Coherent signal processing is done to attain high spatial resolution. However due to this coherent nature of signal, a grainy type of noise is inherent in the image, which degrades the radiometric quality of the data. This is known as the speckle noise whose characteristics are described in detail in [1][2][4][5].

SAR being a radar imaging data is different from the visible images which are obtained by passive optical sensors. SAR utilizes the microwave band in the Electromagnetic Spectrum, to image the scene of interest. Thus, the frequency used is in the lower frequency zones mostly in the 1-10 GHz region. Microwaves have special properties that are important for remote sensing. Because of their longer wavelengths, compared to the visible and infrared bands, microwave radiation can penetrate through cloud cover, haze, dust, and all but the heaviest rainfall, as the longer wavelengths are not susceptible to atmospheric scattering which affects the shorter optical wavelengths. This property allows detection of microwave energy under almost all weather and environmental conditions so that data can be collected at any time. The relatively good spatial resolutions of modern day spaceborne SAR sensors of around 3m and better, have furthered the scope of different applications. However, the potential application in the areas of agriculture, land use type discrimination, forestry biomass estimation, geology, flood mapping, disaster zone mapping, marine biology etc. is affected due to the inherent speckle noise in the data. Due to this noise, the accuracies of image analysis tools involving classification, segmentation, texture analysis, target detection etc get reduced. Apart from that, the automated means of target detection, clustering etc become less efficient, and the end applications suffer.

Speckle noise is a multiplicative kind of noise. This type of noise is inherent in all coherent imaging systems such as LASER(Light Amplification by Stimulated Emission of Radiation), USG(Ultra SonoGram) and SAR imagery. This noise is a result of the random interference between the coherent returns for such an active imaging sensor. The speckle response is represented as:

$$S = x * \eta \qquad (1)$$

Where S is the output scattering coefficient of a target, x its true value, and η is the speckle noise tarnishing the input signal. Fully developed speckle noise has the characteristic of multiplicative noise as shown by G April et al[4].

Different techniques are employed to remove this kind of noise. Denoising technique attempts to remove noise irrespective of the spectral content of the noisy signal. The basic aim of the filtering is to improve the backscattering coefficients in homogeneous areas and the edges in the images too. In addition, the filter should preserve the spatial variability. i.e. the textural information for areas with texture (like forests). The challenge thus, lies in cleaning the image without sacrificing the geometric resolution.

Several denoising techniques based on spatial domain as well as frequency domain exist which are used by researchers. Since speckle is a coherent type of noise, which is multiplicative in nature, general noise removal techniques which are effective for additive noise present in optical images do not work effectively for such data. Noise removal techniques for optical images which are afflicted by Additive White Gaussian Noise (AWGN) are ideal low pass filtering(LPF), Butterworth low pass filtering, Gaussian low pass filtering, which remove the low frequency noise present in such data sets. Simple low-pass filtering processes tend to enhance the radiometric quality at the cost of geometry (effective geometric resolution). If further enhancement is required then high pass filtering(HPF), un_sharp masking, high boost filtering, Laplacian filtering etc are resorted to. In the case of multiplicative noise, which is present in SAR data sets and in some medical imaging data sets, neither LPF nor HPF is effective. Even band pass filters are not effective. Such images are mostly improved by spatial domain statistical filtering techniques such as median filtering. However, they are poor at preserving edges.

One method of noise reduction is the multilook technique during SAR data processing. Here the signal bandwidth is broken up into smaller segments(with or without overlap), and these smaller bandwidth signals are processed in the frequency domain, as usual in the SAR signal processing, and after that these are incoherently summed up to get the output with better radiometric resolution, i.e. less noise. However, the spatial resolution is degraded.

For N look processing the effective spatial resolution becomes N times the original spatial resolution, while the radiometric resolution is improved by a factor of $\sqrt{N}$.

Adaptive filters adapt their weightings across the image to the speckle level, while non-adaptive filters apply the same weighting uniformly across the entire image. Such filtering also eliminates actual image information, in particular, the high-frequency information. The applicability of filtering and the choice of filter type involves tradeoffs. Adaptive speckle filtering is better at preserving edges and details in high-texture areas (such as forests or urban areas). Several such filters such as Lee, extended Lee, extended Frost, Kuan, Gamma-MAP etc are extensively used for SAR denoising as shown by Lee et al, Frost et al, and Baraldi et al in [6-10].

During the last decade Wavelet-based techniques are finding applicability in noise removal due to their space-frequency localization capability. Wavelets have been in use since the last decade for various signal and image processing tasks. The time-frequency domain analysis scope renders such technique very useful in the domains of signal processing, image compression, denoising, image enhancement, resolution enhancement, fractals etc. The fundamental idea behind this is to analyse the signal according to scale. Wavelet transforms have advantages over traditional Fourier transforms for representing functions that have discontinuities and sharp peaks, and for accurately deconstructing and reconstructing finite, non-periodic and or non-stationary signals, as discussed in detail by Mallat[11]. As the processing is performed at various scales there is tremendous scope of feature analysis at the different scales. Thus wavelets are well suited to handling data with sharp discontinuities. This is the feature which makes it extremely suitable for filtering noise, and also in detecting objects. Wavelet based denoising schemes involve non linear thresholding of wavelet coefficients in time-scale transform domain, whereby the noise frequencies are eliminated/ suppressed, as discussed by Argenti et al [12], Gagnon et al[13], Hou et al[14]. Many types of wavelet functions have been in use, out of which the discrete wavelet transform (DWT) which transforms digital signals to discrete coefficients in the wavelet domain, has good capability for signal and image processing applications.

Many papers during this period reported results of wavelet based filtering on SAR as well as medical data sets using several techniques developed, and by extending the original ideas. Some of the results have been reported by P.U Fangling et al, in 2001[15], Solbo et al [16], Gleich et al[17]. S Parrilli et al in 2012 proposed a nonlocal SAR image denoising algorithm based on LMMSE wavelet shrinkage[18]. A novel despeckling algorithm for SAR images has been proposed in the paper by Parrilli[18], based on the concepts of nonlocal filtering and wavelet-domain shrinkage. It follows the structure of the block-matching 3-D (BM-3D) algorithm, which was proposed, for additive white Gaussian noise denoising[19]. At present, BM-3D is considered to be the state of the art for AWGN denoising. Most of the filtering techniques in the wavelet domain operate in a homomorphic way for the SAR data, whereby the linear domain data is logarithmically transformed. Log transform of SAR data, however, changes the basic characteristics of the SAR image, and after speckle removal and inverse logarithm, cannot be retrieved back, as has been reported by Ulaby et al[20].

In our study, an approach has been taken to perform wavelet based denoising on the linear domain SAR image data. As the existing threshold determination approaches are unsuitable for such data, we propose a heuristic approach arrived at based on the analysis of variance of the sub-bands of the wavelet decomposed data.

Approaches to evaluate various filtering techniques including wavelet based methods have been discussed by Gagnon [21]. It is observed that although the evaluation of filtering techniques for optical images is quite standard and universal, there is an apparent disparity of ideas amongst researchers when it comes to evaluating denoised data from SAR having multiplicative signal dependant noise. Several quality parameters such as signal-noise-ratio(SNR), peak signal-noise-ratio PSNR, mean squared error(MSE), signal/MSE (S/MSE) etc are popularly used for evaluating the performance of the denoising techniques[21]. Most of these are quite suitable in the optical image processing domain. However, when SAR data denoising is being looked into, the criteria is different and the above parameters generally are not sufficient for getting the optimal evaluation of the filter in terms of both the radiometric and geometric fidelity. Hence a need exists for exploring an objective way of evaluating denoising to gainfully use the wavelet approach.

For this study we have used the compact support orthogonal wavelet functions of the Daubechies[22]. With the main goal of arriving at an optimal number of decomposition levels, and order of wavelet suitable for denoising C-band SAR data, the RISAT-1(Radar Imaging SATellite) instrument operating in FRS-1(Fine Resolution SAR) mode has been considered, in this study.

The next section describes the wavelet framework for denoising, and addresses the pros and cons of existing thresholding approaches to arrive at a heuristic approach suitable for SAR imagery. The specific datasets suitable for the analysis, and the detailed analysis with different levels of decomposition, and orders of wavelets to arrive at an optimal approach is brought out in section3. The last section summarises the analysis carried out to arrive at the conclusions.

II. WAVELET FRAMEWORK FOR DENOISING

Recent trend in denoising is to use wavelet based techniques, which has the advantage of multi-resolution signal analyzing capability which is beneficial for handling speckle type of noise. Discrete Wavelet Transform is used to transform the digital signals in the image to discrete coefficients in the wavelet domain. The outputs of the low pass filter are known as the *approximation coefficients*, while those from the high pass filter are called the *detailed coefficients*. Some of the mother wavelet and scaling coefficients for Daubechies[22] are shown in Figure2.1. The black curves show the scaling coefficients while the blue curves correspond to the wavelet coefficients for the particular order wavelet. As is shown Fig2.2, the wavelet transform is used to decompose an image into sub-bands, and this can be repeated to multiple levels. Thus at each level of decomposition, the image signal is decomposed into four sub-bands, consisting of the approximation component which is the LL component, and the detailed components (i.e. LH, HL and HH). The detailed parts contain the high frequency components which are mostly tarnished by noise. The LL part can be again decomposed using the above technique, and filtering done till the desired results are obtained. The schematic of the hard thresholding and soft thresholding is given in Fig 2.3. A SAR image and its decomposed version with one level of decomposition are shown in Fig: 2.4.

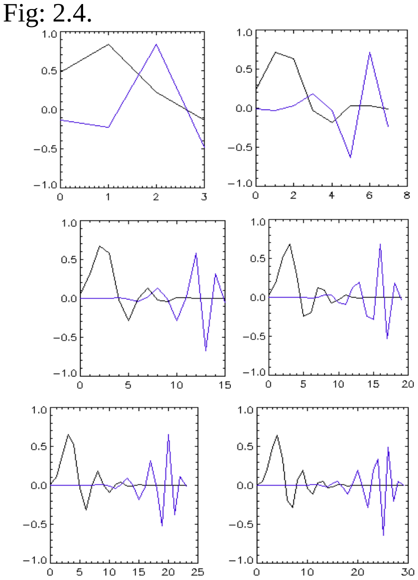


Fig:2.1 Daubechies 4, 8, 16, 20, 24, 30 Scaling & Wavelet Coefficients

The method used for denoising using Wavelets involves the following steps:

(i) Discrete wavelet transform is applied on the data sets to get the sub-bands. The detailed wavelet coefficients are taken for denoising at any decomposition level.

(ii) Thresholding criteria is used to suppress the noise. There are two methods of thresholding (figure 2.3) viz. hard thresholding given in equation 2 or soft thresholding given in equation 3[11].

(iii) After thresholding on one level, further levels of decomposition may be attempted based on the denoising desired, and the above procedure is repeated on the approximate coefficients.

(iv) After going through the desired number of decompositions, the thresholded values are taken through inverse wavelet transform, through all the levels. Final reconstructed image gives the denoised image.

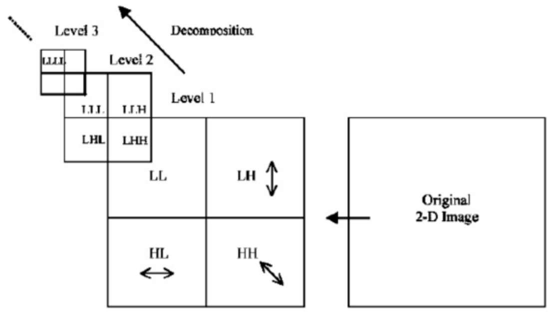


Fig: 2.2 Wavelet Transform Based Decomposition

$$D(Y,\lambda) \equiv \begin{cases} Y & \text{if } \| Y \| > \lambda \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

$$D(Y,\lambda) \equiv \begin{cases} sign(Y)(\| Y \| - \lambda) & \text{if } \| Y \| > \lambda \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

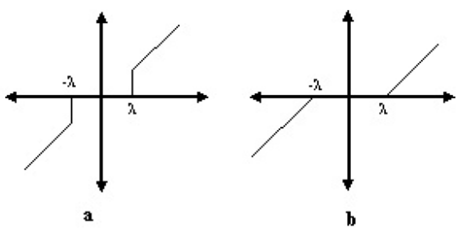


Fig:2.3 (a) Hard Thresholding (b) Soft Thresholding

2.1 Traditional Noise Removal Techniques

The coefficients of the wavelet transform are usually sparse. That is, coefficients with small magnitude can be considered as pure noise and may be set to zero in order to denoise the data. The detailed wavelet coefficients are compared with a threshold value in order to decide whether it constitutes a signal or a noise, and is known as wavelet thresholding. Donoho and Johnstone in 1995 [23], proposed a method to reconstruct a function **f** from a noisy data set **d**. This was done by translating the empirical wavelet coefficients of **d** towards 0 by an amount given by:

$$X = \sigma \sqrt{(2log(n)/n)} \quad (4)$$

Where n is the number of data points in the signal, and σ is the noise or standard deviation in the data which is given by an estimate in the wavelet domain as :

$$\sigma^2 = [(median\ |Y_{ij}|\ ) / 0.6745]^2 \quad (5)$$

where Y_{ij} denotes the coefficients in the HH subband.This was found to be quite effective for Additive White Gaussian noise(AWGN) which is found in optical data. Subsequently several shrinkage methods for soft thresholding have been proposed by researchers. SURE(Stein's Unbiased Risk Estimate) technique whereby the universal threshold is replaced by an adaptive SURE based thresholding which is reported to give better denoising as was reported by Zhang et al[24], and Thierry et al[25]. This also was found out to be highly efficient for optical images. Chang et al, in 2000[26] proposed a novel concept of denoising and compression of optical images by an adaptive, data-driven threshold for image denoising via wavelets based on soft-thresholding. The threshold was derived in a Bayesian framework, and the a priori model used on the wavelet coefficients was the generalized Gaussian distribution (GGD) which is widely used in image processing applications. The proposed thresholding is adaptive to each subband since it depends on estimates of the parameters from the data. Experimental results show that the proposed method, called *BayesShrink*, is typically within 5% of the Mean Square Error(MSE) of the best soft-thresholding benchmark with the image assumed known. It is reported that it outperforms Donoho and Johnstone's[23], *SureShrink* most of the time. Xie et al in 2002[27] reported speckle reduction for SAR using wavelet denoising and Markov Random Field(MRF) Modeling. Using MRF has been popular in the field of image processing and this was extended to SAR denoising. In this paper, a technique is developed for speckle noise reduction by fusing the wavelet Bayesian denoising technique with Markov random-field(MRF)-based image regularization. Experimental results showed that the proposed method outperformed standard wavelet denoising techniques in terms of the signal-to-noise ratio and the equivalent-number-of-looks (ENL) measures in most cases. It also achieves better performance than the refined Lee filter. It has been observed that model-based despeckling mainly depends on the chosen models. Bayesian methods have been commonly used as denoising methods, where the prior, posterior and evidence probability density functions are modeled as illustrated by Chang et al[26]. A novel approach to using SURE based shrinkage to optical image data denoising was proposed by Blu et al in 2007[28]. Using the SURE and LET (linear expansion of thresholds) principles, it was shown that a denoising algorithm merely amounts to solving a *linear system of equations* which is fast and efficient. The very competitive results obtained by performing a simple threshold (image-domain SURE optimized) on the un-decimated Haar wavelet coefficients showed that the SURE-LET principle has a huge potential. Since SAR has multiplicative noise, the method adopted in the reference papers is that of homomorphic approach whereby the logarithm of the data is taken, to force the data into the additive domain. Subsequently the generic denoising filters are applied on those transformed data. Log transform for SAR data, however comes at a cost, as has been reported by Ulaby et al[20]. This transformation changes the basic characteristics of the SAR image, and after speckle removal and inverse logarithm, cannot be retrieved back.

2.2 Methodology

In this study we have adopted an approach to arrive at a suitable thresholding criteria, selecting an optimal order of the mother wavelet chosen, and then arriving at a suitable level of decomposition of the same using all the above criteria in order to get the most optimum image denoising in terms of both geometry and radiometry. The criteria which have been taken into consideration in this study are:

--- Thresholding choice
--- Order of wavelet
--- Levels of decomposition

(a)Threshold Selection Technique

To arrive at a simple threshold derivation for SAR data, the behaviour of the wavelet packet statistics was analysed in terms of level and component (LH, HL,HH) for a number of images containing different types of features (urban, rural, extended targets). It is interesting to note that here we have taken the raw amplitude data of the images without converting them to transform domain (i.e. by taking logarithm), and we have studied the trends of the standard deviations of the sub-bands after DWT.

Typical behaviour and relationship between the components and levels is summarised in Table 2.2.1.

Rural areas have contrasting and a wide variety of features but with less specular areas. Urban image with built up areas, bridges etc and the corner reflectors(CR), is having highly specular features and with high backscattering properties. The Sunderban area is having very low backscatter with very little variation. Table 2.2 shows the trends of the standard deviation of the various sub-bands for different levels of decomposition for the three data sets chosen.

Table 2.2.1 Standard Deviation of the Sub-bands

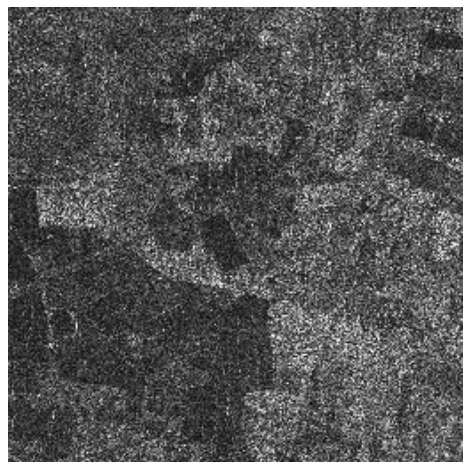
	LH	HL	HH
Abd_Rural			
Level 1	98.37	124.75	64.42
Level 2	194.81	199.73	149.93
Level 3	310.52	266.92	231.72
CR_Area			
Level 1	427.43	432.45	207.66
Level 2	1125.71	1008.13	598.54
Level 3	2088.54	1767.63	1355.45
Sunderban			
Level 1	22.10	20.65	18.92
Level 2	25.92	24.43	22.45
Level 3	32.93	28.23	26.64

Typical rural and urban areas show a behaviour where LH and HL sub-bands have a standard deviation(SD) of about two times the standard deviation of the HH sub_band. Further, as the levels of decomposition go up the SD seems to be almost doubling.

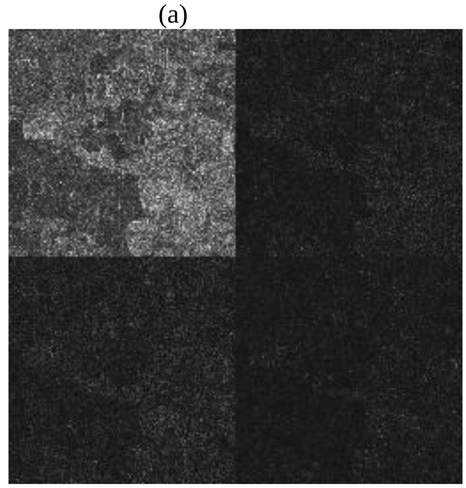
However, the flat Sunderban area shows low standard deviation for all the sub-bands and for all levels of decomposition.

Thus it may be said that the overall SD depends on the scene content and hence the urban area with CR is showing very high SD, while a less specular area with typical rural features have lesser SD, which is almost $1/4^{th}$ that of the urban scene. This is in contrast to that of optical images having additive noise, where such trend is normally not observed. Hence typical threshold selection techniques do not give consistent results for denoising SAR types of data.

So, here, we propose a simple heuristic method to select the threshold for denoising, whereby the threshold is selected as $k * \sigma_s$, where σ_s is the standard deviation of the sub-bands for the first level of decomposition. We have found that the typical value of k is about 4 for consistent results, for all the above types of data sets chosen for our study.

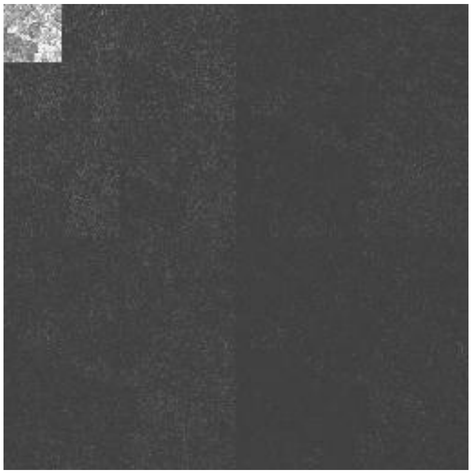


(a)

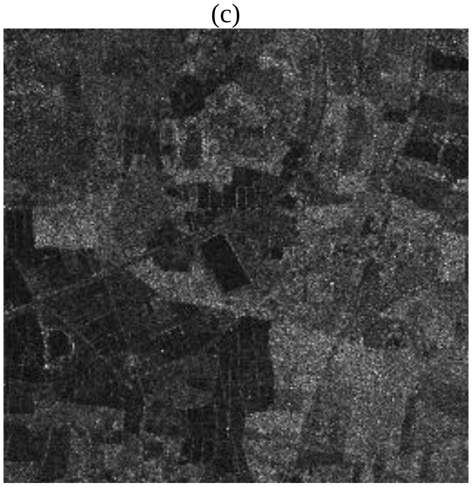


(b)

Fig:2.4(a) SAR Image of FRS-1, RISAT-1
Fig:2.4(b) 1 Level Decomposed Image showing LL, LH, HL & HH sub-bands



(c)



(d)

Fig:2.4(c) 3 Level Decomposed Image
Fig:2.4(d) Denoised Image with 1 level decomposition

(e)

(f)

Fig: 2.4(e) Denoised Image with 2 level decomposition
Fig:2.4(f) Denoised Image with 3 level decomposition

Sr No	Type	Point Target 1		Point Target 2	
		Range(m)	**Azimuth(m)**	**Range(m)**	**Azimuth(m)**
1	**Raw**	3.44	3.63	3.70	3.16
2	**Lee3**	4.62	5.35	4.70	5.48
3	**Lee5**	5.07	8.67	8.42	8.36
2	**D4**	3.36	3.28	3.79	3.24
4	**D8**	3.32	3.80	5.27	5.28
5	**D16**	4.26	4.57	3.88	4.05
6	**D20**	3.64	4.07	4.80	4.49
7	**D24**	3.56	4.28	4.14	4.46

(b) Order Selection Technique

Filtering is done for one level of decomposition for the different orders of the mother wavelet (Daubechies) i.e. for D4, D8, D16, D20 and D24. Spatial resolution and the structural/shape function of the CRs deployed in the study were estimated, on the denoised images. For the same orders of the mother wavelet we also estimated the radiometric resolution of some of the uniform zones in the rural areas. Based on this study we found that there is very little impact of the order of the particular mother wavelet chosen, on the quality of the image. This is shown in Table2.2.2.

So for subsequent analysis, it was decided to take only the two orders viz. D4 and D24.

Table 2.2.2 Spatial Resolution for CRs (from IRF)

(c) Levels Of Decomposition Selection

Based on the results of the analysis of order selection, the analysis is carried out for more levels of decomposition. After analysing further levels of decomposition results we come to a logical conclusion about the optimal choice of number of levels of decomposition for noise removal in the SAR context.

III. DATA SELECTION

India's RISAT-1 satellite carries a C band active array antenna with a capability to acquire data in different modes of acquisition and with quad-polarization capability [29-30]. There are five major modes of operation. These are:

1. High Resolution Spotlight Mode (HRS): It provides 1m azimuth and 0.7m slant range resolution over a spot of 10Km x10Km. There is a provision for sliding spotlight image of 100 km (azimuth) X 10 km (range) on experimental basis also.

2. Fine Resolution Strip map Mode-1 (FRS-1): It provides 3m azimuth and 2m slant range resolution over 25Km swath.

3. Fine Resolution Strip map Mode-2 (FRS-2): It provides 9m azimuth and 4m slant range resolution over 25Km swath.

4. Medium Resolution ScanSAR Mode (MRS): It provides 24m azimuth and 8m slant range resolution over a swath of 120 Km.

5. Coarse Resolution ScanSAR Mode (CRS): It provides 50-60m azimuth and 8m slant range resolution a over swath of 240Km.

Apart from the dual and multi polarization modes of operation there is a unique capability to have hybrid polarimetric mode of data where signal is transmitted in circular polarization and signal is simultaneously received in H and V polarization. In this mode the complete Stokes parameter can be generated from which all the polarization components of odd bounce, even bounce and volume scattering can be constructed. This feature is a complimentary feature to full-polarimetric SAR mode of operation with an added advantage of retaining a bigger swath as discussed in detail by Misra et al[28][29]. The major specifications are summarized in Table 3.1 The payload modes of operation with the respective resolution and swath are highlighted in Table 3.2

Data with a nominal resolution of around 3m has been chosen for this study. Different types of data have been chosen for the analysis so as to cover most of the scattering mechanisms with its embedded multiplicative noise. As speckle noise is data dependent, different types of regions were selected in order to establish the veracity of the filtering and the qualitative performances. Fine resolution mode of data of 3m gives us ample scope to see the capacity of the filtering to reduce noise without degrading the resolution.

Three datasets have been selected for the analysis:

- One data set has been chosen over the rural Ahmedabad region, having field regions with distinct boundaries, roads and different types of textures.
- Second data set is over an urban area in Ahmedabad, with bright scatterers such as bridges, buildings, man-made structures etc. Some corner reflectors(CR) used for calibration are also chosen for analysing the point target response.
- Third data is selected to be a fairly homogeneous (flat) area over the Sunderban region in West Bengal, which is the mangrove forest well known for its uniform back scattering signatures for SAR which is normally useful for calibration purpose. Distinct uniform land mass and water bodies are its features.

For this particular study only Daubechies wavelets have been used. Threshold selection criteria was based on the images shown in Figures 3.2(a) (b) and (c).

Table 3.1 RISAT-1 SAR Major Specifications

Parameter	Value
Orbit	Circular Polar Sun-synchronous
Orbit Altitude	536Km
Orbit Inclination	97.552^0
Orbit Period	95.49 minutes
Number of Orbits per day	14
Repetivity	25 days
Frequency Band	C band(5.35GHz)
Polarization(selectable)	Single, Dual, Quad, Hybrid Polarimetry
Look Angle of operation (selectable)	9^0 - 47^0
Modes of Operation	Stripmap Scansar (Medium) Scansar (Coarse) Spotlight
Antenna(Microstrip)	6m X 2m
Swath	10 – 220Km
Resolution	1m - 50 m

Table 3.2 RISAT-1 SAR Modes/Resolution

P/L Modes	Swath (Km)	Resolution (m)
Coarse Resolution ScanSAR Mode(CRS)	220	50
Medium Resolution ScanSAR Mode(MRS)	115	25
Fine Resolution Stripmap Mode(FRS-1)	25	3
Fine Resolution Stripmap Mode Multi-polarization (FRS-2)	25	9
High Resolution Mode(HRS)	10	1

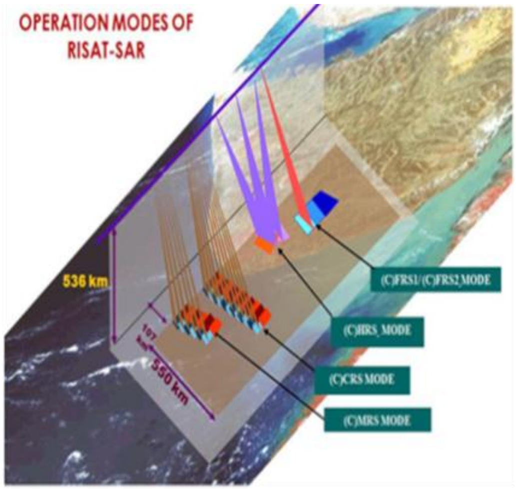
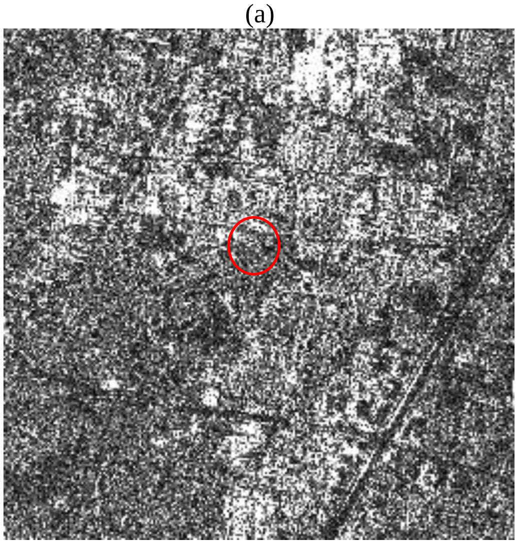
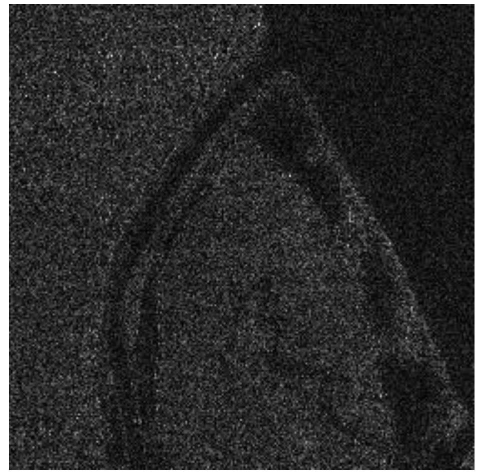


Fig 3.1 Illustration Of Imaging Modes of RISAT-1

(a)



(b)



(c)

Fig 3.2(a) Abd_Rural, (b) Urban with CR(within red circle) and (c) Sunderban mangrove region

In the following sections we are showing the results of analysis carried out on the CR data and the homogeneous data extracted from the Ahmedabad rural areas, in order to determine suitable order of Daubechies wavelet, and level of decomposition. Quality parameters are the spatial resolution and radiometric resolution. In terms of these parameters the performances will be compared with the original and conventional non wavelet based filter such as Lee filter.

The rural image with different levels of decompositions, and its denoised images with Daubechies-D4 coefficients, for Level 1, 2 and 3 have been shown for illustration purpose in Fig2.4.

Quality measurement criteria and performance analysis were reported by A Misra et al in [30][31]. A detailed review of various denoising techniques for SAR data was published by Arundhati et al, in [32]. In a recent paper by V S Rathore[33], the simulation steps of hybrid filter model that consists image denoising and image enhancement implementation over three different noises such as Salt and Pepper noise, Gaussian noise, Speckle noise with different noise variance in the range 0.02 to 0.14 is given. Hybrid filter works on spatial filtering techniques such as median filter and high pass filter that is operated on neighbourhood pixels. For analysis they have used the standard PSNR, MSE, and SNR. This is done on simulated noise, hence the above quality parameters are sufficient. For actual SAR images with unknown speckle, radiometric and geometric resolution criteria as adopted in our paper is the optimal choice.

IV. Results Of Analysis

In this section we present the results of analysis carried out on the CR data and the homogeneous data extracted from the Ahmedabad rural areas, in order to determine suitable order of Daubechies wavelet, and level of decomposition.

Quality parameters are the spatial resolution and radiometric resolution. These parameters are used for evaluating the geometric quality and radiometric quality of the images after denoising.

4.1 Spatial Resolution Evaluation

Spatial quality is evaluated using CR image in range and azimuth directions using the Impulse Response Function(IRF). Table 4.1 shows the range and azimuth resolutions for one point target, which is the corner reflector(CR) shown encircled in red, in Fig3.2(b). This is done for different orders of Daubechies wavelet based filtering and for Lee filtered data, and for different levels of decomposition for the wavelet based filtering. The snapshots of the extracted CR raw image and the filtered images are shown in Fig 4.1

For the different orders of wavelets, for Level-1 decomposition, it was observed that D4 to D24 gave almost similar spatial resolutions, So, it was decided to keep only D4 and D24 for further studies using Level 2 and 3 decomposition. The chips shown in Fig4.1 for the level 2 and 3 decomposition, show more blurring of the point target, for D8, D16, D20. D4 and D24 are less degraded. So D4 and D24 were taken for seeing the results of more levels of decomposition using the quantitative evaluation of the range and azimuth resolutions. The values are shown in Table4.1. It is observed that D4 shows very less degradation in the resolution for the different decomposition levels. D24 gave degraded resolution with higher levels of decomposition as is expected.

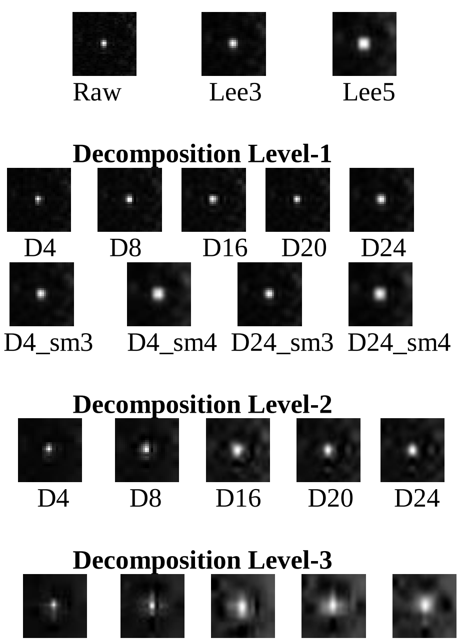
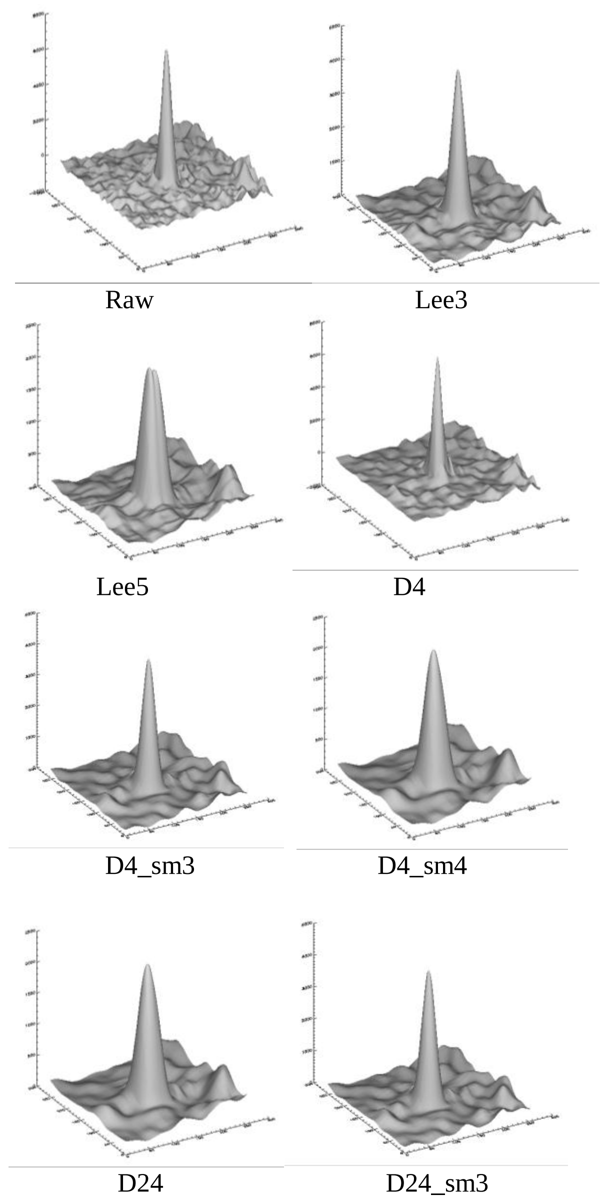
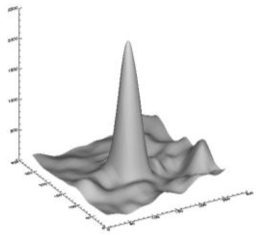


Fig:4.1 CR images for raw & different filtering methods and for different levels of decomposition

Table 4.1 Spatial Resolution (from IRF of Point Target) CR Area

No		Level 1		Level 2		Level 3	
		Range (m)	Azimu th(m)	Range (m)	Azimu th(m)	Range (m)	Azimu th (m)
1	**Raw**	3.7038	3.1646	--	--	--	--
2	**Lee3**	4.7081	5.4859	--	--	--	--
3	**Lee5**	8.4277	8.3678	--	--	--	--
4	**D4**	3.7964	3.2444	3.8520	3.3183	3.7720	2.9675
5	**D24**	4.1438	4.4617	7.6068	6.3020	8.6730	11.577
6	**D4_sm3**	5.3082	5.4557	--	--	--	--
7	**D24_sm3**	5.2089	5.7333	--	--	--	--
8	**D24_sm4**	7.4494	7.4200	--	--	--	--





D24_sm4

Fig:4.2 Decomposition Level 1 – Point Target Response

It is seen that D4 gives the best resolution for all levels of decomposition, both from the values and from the images. However, if we see the actual 3D response of the target, it is observed that the IRF gets distorted in D4. This is shown in Fig4.2. Only D24 preserves the 3D features well. This prompted us to study some additional post processing method on the wavelet denoised data sets to see if the fidelity of the targets could be improved or not. An additional box car filtering on the D4 and D24 filtered images was performed which are denoted as D4_sm3, D24_sm3 etc. It is seen that this gives good shape fidelity although slightly degraded spatial resolution. Though D24 and D4 followed by a simple box_car filtering, gives resolution values which are comparable, the 3D plot shows that filtering with D24 preserves the shape better than D4 filtered image. It is also observed that with more levels of decomposition the point target gets more and more blurred. In higher levels of decomposition, smoothing is inherent in the filtering and hence additional smoothing is not required. Smoothing window size is used as the naming convention, such as, ‘sm3’ indicates a window size of 3, and so on. However, to assess the quality of filtering, another crucial criteria is the radiometric quality. This is given in section 4.2.

4.2 Radiometric Resolution Evaluation

For the evaluation of radiometric quality of the images most of the earlier studies report MSE and SNR as the parameters. However, for SAR type of data MSE may not be giving the proper indication as reference data without noise is not possible to get. For SAR better quality index is the radiometric resolution of a relatively homogeneous region with medium back scattering.

For this study, homogeneous areas from the fields of Ahmedabad rural scene have been chosen, and radiometric resolution is evaluated for the raw and the filtered data sets. We are showing the results of one typical area. Snapshots of the area and results of the filtering are shown in Fig4.3 and Table4.2, respectively.

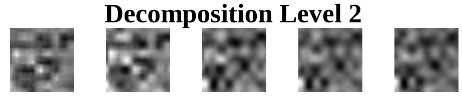
Raw Lee3 Lee5

Decomposition Level 1

D4 D8 D16 D20 D24

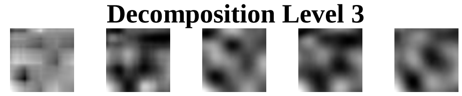
D24_sm3 D24_sm4 D4_sm3 D4_sm4

Decomposition Level 2



D4 D8 D16 D20 D24

Decomposition Level 3



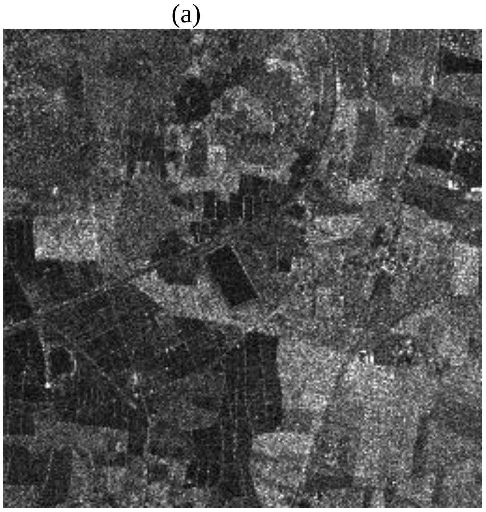
D4 D8 D16 D20 D24

Fig:4.3 Uniform area images of raw & different filtering methods for different levels of decomposition

Table4.2: Radiometric Resolution for Uniform Area

Image Type	Level-1		Level-2		Level-3	
	Mean	**Rad Resln (dB)**	**Mean**	**Rad Resln (dB)**	**Mean**	**Rad Resln (dB)**
Raw	168.13	3.75491	--	--	--	--
Lee3	167.31	1.99339	--	--	--	--
Lee5	166.82	1.41320	--	--	--	--
Daub4	167.81	2.56500	165.99	1.6593	166.81	1.0595
Daub8	166.79	2.57482	166.37	1.6668	166.43	0.9623
Daub16	167.82	2.65680	167.17	1.7520	165.89	1.1984
Daub20	167.30	2.59149	167.21	1.8184	166.44	1.0524
Daub24	166.83	2.61575	166.94	1.8641	166.73	1.0252
Daub4 +sm3	167.34	1.83145	--	--	--	--
Daub4 +sm4	166.92	1.34469	--	--	--	--
Daub24 + sm3	166.93	1.92252	--	--	--	--
Daub24 + sm4	167.13	1.37500	--	--	--	--

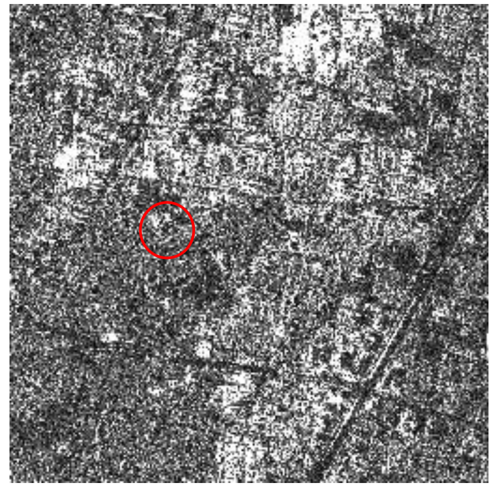
(a)



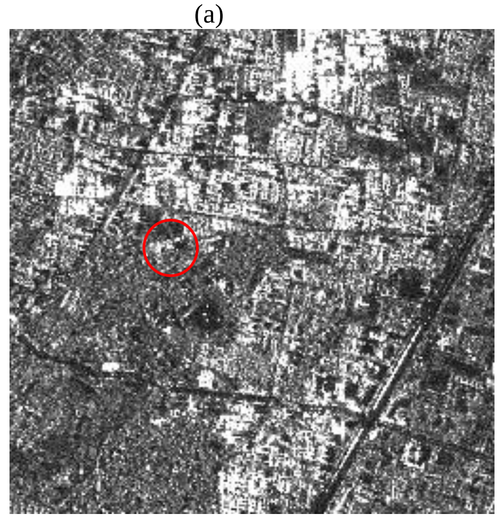
(b)

(c)

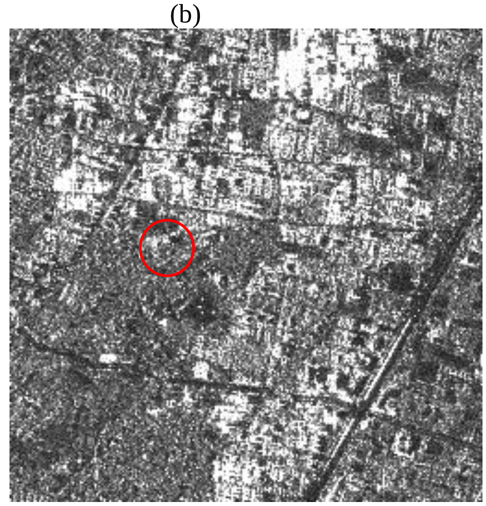
Fig: 4.4(a) Abd_rural images for raw (b) D4_sm3 (c) D24_sm3 for 1 level of decomposition



(a)



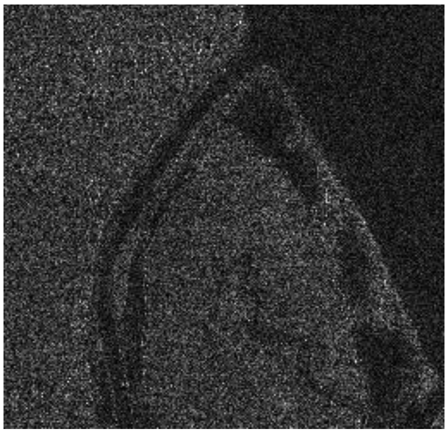
(b)

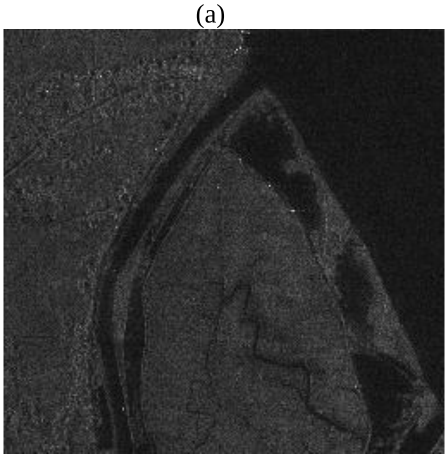


(c)

Fig:4.5 (a) CR images for raw, (b)D4_sm3 (c)D24_sm3 for 1 level of decomposition

The raw data has uniform texture, but is specular in nature. With filtering, the noise gets reduced. As levels of decomposition go higher, there is a consistent improvement in radiometric resolution for all Daubechies filters, but the image gets more blurred. As was shown in the earlier section the spatial resolution gets poorer. The raw data for all the chosen data sets are shown in Fig4.4(a), Fig4.5(a) and Fig4.6(a). The final images with wavelet based denoising using the techniques, discussed here are shown in Fig4.4(b)&(c), Fig4.5(b)&(c), Fig4.6(b)&(c)


(a)


(b)

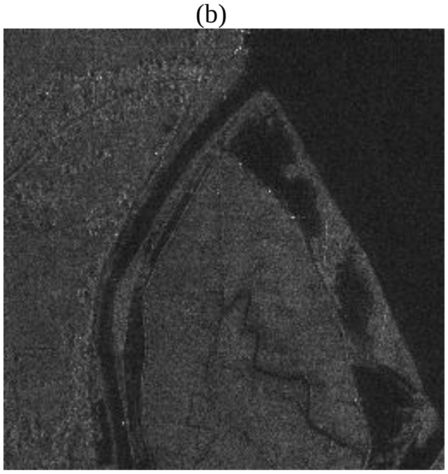

(c)

Fig:4.6(a) Sunderban images for raw, (b) D4_sm3

(c) D24_sm3 for 1 level of decomposition

In all the cases, the mean is preserved and the radiometric resolution, which is the poorest in the raw image, and is about 3.75dB, is improved by the filtering. D24 with Level3 decomposition gives the best radiometric result of about 1.02dB. But three levels of decomposition blurs the data drastically, which is not desirable. As was discussed in previous section, post processing of the images using wavelet filtering was resorted to in order to see, if any improvement can be achieved. It is seen that with only one level of decomposition followed by box car smoothing, we can achieve about 1.92dB for D24 with sm3, and 1.83 for D4 with sm3. This also preserves the geometric fidelity of the target.

Finally, the analysis shows that combining the spatial and radiometric resolution quality parameters along with the 3D profile evaluation for CR type targets, filtering with D24 followed by a box car smoothing of window size 3, with just one level of decomposition, is sufficient to give good performance on all the chosen images. It is interesting to note that the radiometric resolution improvement at the cost of spatial resolution degradation for higher levels of decomposition can be avoided by the above simple technique. This gives comparable or sometimes better results as compared to the spatial domain adaptive filters.

It is also observed that D4 gives good spatial resolution, but after a critical look at the 3D behaviour of the impulse response function, it was found that the geometric fidelity is not preserved well. However, after doing the box car smoothing on the same the fidelity had improved. As the D24 did not have this problem and at the same time gives consistent result, it is recommended as the optimal one for the types of data sets taken in this study. The area marked in circle shows the CR data, which become distinctly visible after the denoising.

CONCLUSION

Wavelet based techniques have been gaining importance in the field of SAR data denoising during the past few years. SAR sensor, due to its inherent coherent processing has noise characteristics which is different from those of visible images and hence needs different ways of filtering. Factors influencing denoising of images are the order of the mother Wavelet, decomposition level, thresholding and shrinkage criteria chosen. The approach depends on the suitability of performance in terms of geometric and radiometric quality of the images. In this paper we have considered Daubechies class of wavelets for denoising. Performance on RISAT-1 C band, fine resolution SAR data was carried out to arrive at a suitable order of the wavelet, decomposition level and thresholding criteria. Corner reflector images have been used for measuring the geometric quality, while uniform target areas have been chosen for assessing the radiometric quality. Approach for thresholding selection is derived by studying the behaviour of wavelet components of the sub-bands, and a heuristic approach is arrived at based on that. It is found that for the selected SAR data sets, the optimal order is Daubechies24 and the level of decomposition is one, if followed by a simple box car smoothing. The above analysis is done on the linear domain of the full 16bit dynamic range of SAR amplitude data instead of dealing with log transformed images. The order of geometric resolution achieved is about 5m, and the radiometric resolution is about 1.8dB. Depending on the specific end application one may opt for higher levels of decomposition but at the cost of geometric resolution and edge smoothing. More than two levels of decomposition, gives good radiometry but with blurring. The preservation of the geometric fidelity of the corner reflector image after denoising is an added attribute of the above approach, as has been shown in the analysis section. It is to be noted that conventional multilook techniques used for SAR denoising in frequency domain of approach, can generate an equivalent radiometric performance, only at a spatial resolution of about 10m.

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