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A Novel Despeckling Method for SAR Images Based on Simultaneous Sparse Coding and Wavelet Packet Adaptive Thresholding

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ABSTRACT: Speckle is a granular disturbance usually modelled as a multiplicative noise that affects synthetic aperture radar images(SAR) as well as coherent images. This paper propose a SAR image de speckling method based on patch ordering and transform domain filtering. It consists of two stage filtering , first is a coarse filtering stage which can suppress the speckle effectively. In this, extract the sliding patches from the logarithmic SAR image and order them in a smooth way by the patch ordering algorithm .The ordered patches are then filtered by simultaneous sparse coding(SSC) because of their superior noise reduction ability. Then this coarse filtering result is reconstructed from the filtered patches via inverse permutation and sub image averaging. The second stage is refined filtering which can eliminate small artefacts generated by coarse filtering . Here filtering the coarse filtered result by wavelet packet adaptive thresholding. WP decomposition is applied to noisy images to obtain the optimal wavelet basis, utilizing Shannon entropy. It selects an adaptive threshold value which is level –sub band dependent based on the statistical parameters of sub band coefficients and reconstruct the refined result by inverse wavelet packet transform. Experimental results with both simulated image and real SAR image shows that proposed method achieves state-of-the-art despeckling performance in terms of peak signal to noise ratio(PSNR), structural similarity index(SSIM) and mean of ratio images.

KEYWORDS: Synthetic Aperture Radar(SAR), Patch Ordering, Simultaneous Sparse Coding, KSVD dictionary, Wavelet Packet and Optimal Wavelet Basis .

I.INTRODUCTION

Synthetic Aperture Radar (SAR) is a kind of radar which uses signal processing to improve the resolution beyond the limitation of physical antenna aperture [2]. In SAR, forward motion of actual antenna is used to 'synthesize' a very long antenna so its name comes as synthetic aperture radar. Synthetic aperture radar (SAR) remote sensing offers a number of advantages over optical remote sensing, mainly the all-day, all-weather acquisition capability[2], high resolution, 2D and 3D mapping, change detection,4D mapping etc. However, the main drawback of SAR images is the presence of speckle, a signal dependent granular noise, that visually degrades the appearance of images[3], give grainy appearance to radar imageries , reduces image contrast which has a direct negative effect on texture based analysis of imageries etc. For these reasons, a pre processing of real-valued detected SAR images aimed at speckle reduction, or de speckling, is of crucial importance for a number of applications. Such a pre processing should be carefully designed to avoid spoiling useful information, such as local mean of backscatter, point targets, linear features and textures[3].In general the speckle in SAR images are characterized by the multiplicative noise model .The purpose of de speckling is to remove the speckle noise. The purpose is to recover the underlying target backscattering coefficient ie de speckled image from the observed intensity image. There are many methods that have been proposed during the past three decades.

In this work, SAR image de speckling is based on patch ordering and two stage transform domain filtering. Here work on the logarithmic SAR images because of better performance of log intensity data .However, this method is different from previous works in the following two aspects. First, here applying transform-domain filtering to the ordered SAR

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patches in first stage. Second, propose a two-stage strategy to both deal with speckle reduction and artefact elimination. Specifically, in the first stage , the main purpose is to effectively remove the noise. Therefore, filter the ordered patches with simultaneous sparse coding because of their superior noise reduction ability combined. Then in the second stage, applying wavelet packet thresholding to the coarse filtered result and reconstruct the refined result. The reason is for using 2 stage transform domain is that any single stage transformation is susceptible to produce artefacts. Different transform basis exploited which is based on the idea that independent transform domain filtering methods will often produce complementary artefacts.

II.LITERATURE SURVEY

Early works on de speckling were deployed in the spatial domain and were obtained by making assumptions on the statistical properties of reflectivity and speckle, e.g., pdf and autocorrelation function .In [4] by J.S.Lee ,an LMMSE solution was derived by linearizing the multiplicative noise model around the mean and variance of the noisy signal. This is the first model based de speckling filter[4].In [5] by V.S Frost, starting from a model of the coherent imaging system, a parametric approximation of the autocorrelation function of reflectivity is derived from local statistics. Kuan's filter [6] exactly implements the LMMSE solution starting from a signal model that features non stationary mean, non stationary variance. disadvantages of adaptive filters are over smooth image texture, ineffective de noising around edges and cannot meet the requirement of easy interpretation and clear classification.

Filtering in the wavelet domain has been extensively used during the last twenty years and potentially superior performances over conventional spatial filters . In [7] by H. Guo et al ,introduces a novel de speckling method based on thresholding the wavelet coefficients of logarithmically transformed image.The nonlocal means (NLM) algorithm proposed by Buades et al. [8] provides a breakthrough in image denoising .In this approach, defining the weights as a function of the Euclidean distance between a local patch centered at the reference pixel and a similar patch centered at a given neighbouring pixel. In Probablistic patch based filter [9] by C.Deladelle, NL filtering has been applied to despeckling by substituting the Euclidean distance used in the NL mean filter with a probabilistic measure that takes into account the pdf of SAR data.On the other hand, image denoising via sparse representation has also attracted an increasing amount of attention. In fact, natural images satisfy a sparse model, that is, they can be seen as the linear combination of few elements of a dictionary or atoms[3]. In [10] by Elad and Aharon, proposed the nonlocal sparse model for image denoising method based on sparse representation over learned the KSVD algorithm. In [11] by Mairel et al , proposed the nonlocal sparse model for image denoising by combining non local method and sparse coding by using simultaneous sparse coding (SSC). Multilevel WP decomposition is applied to noisy images to obtain the best tree or optimal wavelet basis, utilizing Shannon entropy. It selects an threshold value which is dependent on level-subband based on the statistical parameters of subband coefficients[12].

III.DESIGN AND ANALYSIS

The proposed algorithm consists of two stages, coarse filtering and refined filtering .In the coarse filtering stage, the log-intensity SAR image is filtered by patch ordering and SSC. Here taking the logarithm of image because of better performance of log intensity data. Although denoising via SSC can suppress speckle effectively, it produces small artefacts which are caused by the learned dictionary. The artefacts generated by sparse representation can be alleviated by other transform domain methods[1]. To handle this, here adopt a refined filtering stage in which the coarse filtering result is filtered by wavelet packet adaptive thresholding[12].Fig1shows the block diagram of the proposed method of SAR image despeckling and details is shown in Algorithm 1[1][12].

A. Coarse Filtering

In SAR image ,speckle is characterized by the multiplicative noise model

$$I=xv \qquad (1)$$

Where I is the noisy image ,x is the underlying target backscattering coefficient and v is the speckle. Completely developed speckle follows the gamma distribution .

$$\rho_v(v) = \frac{L^{L}v^{L-1}}{\Gamma(\mathrm{L})}\exp(-vL), \quad v \geq 0 \qquad (2)$$

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(ENL) and $\Gamma(\,)$ is the gamma function. For a homogeneous region , the L can be calculated by

$$L = \frac{mean^2}{var} \qquad (3)$$

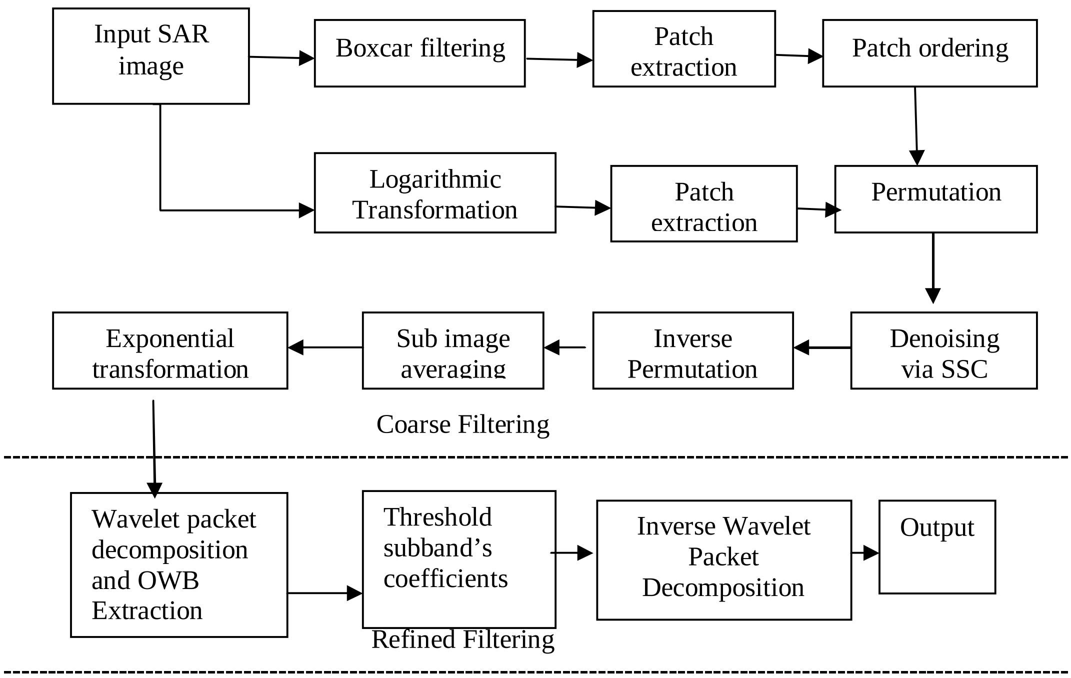

Fig 1. Block diagram of proposed method

This will be fed to the algorithm for removal of bias and setting of filtering parameters[1]. Applying natural log transformation to equation (1) , then it becomes

$$ln(I)=ln(x)+ln(v) \qquad (4)$$

Then the log SAR image with bias correction is

$$I^{(ln)} = \ln(I) - \varphi^{(0)}(L) + \ln(L) \qquad (5)$$

Then the filtering process will work on the bias corrected data $I^{(ln)}$[1] .

ALGORITHM 1 : Proposed Algorithm For Sar Image De-Speckling[1][12]

- **Input** : The input SAR image I , the ENL L.
- **Step 1 : Coarse Filtering**
- **Boxcar Filtering** : Apply a 3x3 boxcar filter to I , obtain the filtering result I_B .
- **Logarithmic transformation with bias correction :** Calculate the log intensity image with $I^{(ln)}$ by taking logarithm transformation with bias correction to I.
- **Patch Extraction :** Extract the sliding patches $\mathbf{Y_1}$ and $\mathbf{Y_B}$ of size $\sqrt{n_1} \times \sqrt{n_1}$ from $I^{(ln)}$ and I_B respectively .
- **Patch ordering :** Order the patches $\mathbf{Y_B}$ by Algorithm 3.2 and obtain the set Ω_1 . Then calculate the ordered patches $\mathbf{Z_1}$ by $\mathbf{Z_1} = \mathbf{Y_1}P_{\Omega_1}$
- **Denoising via SSC :** Denoise $\mathbf{Z_1}$ by Algorithm 3.3 and obtain the filtering result $\widehat{\boldsymbol{Z_1}}$.Then perform inverse permutation on $\widehat{\boldsymbol{Z_1}}$ ie $\widehat{\boldsymbol{Y_1}} = \widehat{\boldsymbol{Z_1}}\, P_{\Omega_1}{}^{-1}$.
- **Subimage Averaging :** Reconstruct the filtering result $\widehat{I_1^{(ln)}}$ from $\widehat{\boldsymbol{Y_1}}$ by subimage averaging.
- **Exponential Transformatiom :** Calculate the coarse filtering resul $\widehat{x_1}$ by applying exponential transformation to $\widehat{I_1^{(ln)}}$.

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➢ **Step 2 : Refined Filtering**

- Perform WP decomposition to obtain OWB of a noisy image by using Shannon entropy.
- Estimate the noise variance
- For each subband S in level d compute the threshold value and statistical parameters

1. Subband's variance ($\sigma^2_{x1,s}$).
2. Subband's mean (μ_s).
3. Estimate the variance of clean image using equation (18).
4. Term $\alpha_{d,s}$ using equation (20).
5. Threshold value using equation (16).

- Threshold all subband coefficients using the proposed threshold technique given in (21).
- Perform inverse WPT to reconstruct the denoised image.

This will be fed to the algorithm for removal of bias and setting of filtering parameters[1]. Applying natural log transformation to equation (1) , then it becomes

$$ln(I)=ln(x)+ln(v) \qquad (4)$$

Then the log SAR image with bias correction is

$$I^{(ln)} = \ln(I) - \varphi^{(0)}(L) + \ln(L) \qquad (5)$$

Then the filtering process will work on the bias corrected data $I^{(ln)}$[1] .

Patch Extraction And Ordering

Suppose that size of I is $N_1 \times N_2$. Here extract the sliding patches of size $\sqrt{n} \times \sqrt{n}$ from $I^{(ln)}$ and I_B. Inorder to improve the accuracy of patch ordering ,a 3x3 boxcar filtering is first applied to I and obtain the filtering result I_B.Let Y_1 and Y_B be the patches extracted from $I^{(ln)}$ and I_B respectively. Let y_i $(i = 1………N^{(p)})$ be the column stacked versions of sliding patches and $N^{(p)}$ be the size of patches[1]. Then ordering the patches in a smooth way.The original patch ordering algorithm [9] utilizes the Euclidean distance as the similarity measurement. But Euclidean distance is not an appropriate choice for SAR images .Here uses block similarity measure (*BSM*) [9] as the similarity measurement[1]. The BSM of y_i and y_l is

$$BSM_{i,l} = \sum_j ln\left[\frac{\sqrt{y_i(j)}}{\sqrt{y_l(j)}} + \frac{\sqrt{y_l(j)}}{\sqrt{y_i(j)}}\right] \qquad (6)$$

For reducing the computational complexity of patch ordering.,drop cycle spinning method and restrict the search range to a C x C neighborhood surrounding the current patch .The patch ordering algorithm for SAR images is shown in Algorithm 2[1].Set *Ω1*is obtained from $\boldsymbol{Y_B}$ by Algorithm 2. Then the ordering and permutation of logarithmic SAR patches Y_1 will still be implemented based on their similarity from the original SAR image.

ALGORITHM 2 : Patch Ordering for SAR images[1]

- **Input**: The image patches $y_i \left(i = 1 .... N^{(p)}\right)$.
- **Parameter** : The search range C x C.

  Choose the first patch as the initial patch ,ie .$\Omega(1)$.
- **for** i = 1 to $N^{(p)} - 1$ do

  Let Q_i and $y_{i'}$ be the current patch and the set of indices of the search range around $y_{\Omega(i)}$ respectively.
- **if** $\left| Q_i / \Omega \right| \geq 1$ **, then**

  Calculate the BSM of y_l and $y_{\Omega(i)}$ where $l \in Q_i / \Omega$ Choose the $y_{\hat{l}}$ patch corresponding to the smallest

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BSM.

- **else**
  Choose the spatially nearest patch $y_{\hat{l}}$ to y_l, where $\hat{l} \notin \Omega$.
- **end if**
  $\Omega(i+1)=\hat{l}$
- **end for**
- **Output** : The set Ω which holds the ordering.

Simultaneous Sparse Coding

In the coarse filtering stage, the ordered patches are filtered by simultaneous sparse representation. The core idea of SSC [13] is that several same signals can be represented by the combinations of the similar atoms. Then de noising several similar patches $\mathbf{z}_i$ $(i \in S)$ amounts to solving

$$\min_{\Lambda}\|\Lambda\|_{0,\infty}\ s.t.\ \sum_{i \in S}\|z_i - D\alpha_i\|_2^2 \ \ \varepsilon^l \qquad (10)$$

where S is the set of similar patches, and $\mathbf{\Lambda}$ is

$$\mathbf{\Lambda}=(\cdot\cdot\cdot\boldsymbol{\alpha_i}\cdot\cdot\cdot)i\in S. \qquad (11)$$

where $\|\boldsymbol{\Lambda}\|_{0,\infty}$ is a pseudo norm[15] which indicates the number of nonzero rows of $\mathbf{\Lambda}$. The K-SVD algorithm[14] can adopted to train the dictionary D by replacing the sparse coding stage in [13] with the SSC problem (10). For log- SAR images,ε^l can be obtained by

$$\varepsilon^l = nN^{(S)}\varphi^{(l)}(L) \qquad (12)$$

where $N^{(S)}$ is the number of elements in set S. In general, the similarity of neighbouring patches in $\mathbf{Z}_1$ is relatively high. Thus, we use $N^{(S)}$ neighbouring patches to form a group and then perform SSC on each group. It should be noted that the l_2 norm used in (12) is not optimal choice for the logarithmic speckle. However, the speckle in log SAR images tends to become Gaussian with the increase in the ENL.Thus, it is reasonable to adopt the l_2 norm.

Then,(10) can be solved by the Simultaneous OMP algorithm[15]. Then the filtering result of $\mathbf{z}_i$ is

$$\widehat{z_i}=D\alpha_i \qquad (13)$$

The de noising method via SSC is summarized in Algorithm 3. Let $\widehat{z_i}$ be the filtered patches obtained by Algorithm1.Then, the coarse filtering result $\widehat{x_1}$ can be reconstructed from $\widehat{Z_1}$via inverse permutation, subimage averaging, and exponential transformation.

Algorithm 3: De-noising via SSC[1]

- **Input :** Ordered patches **Z** , the ENL L.
- **Parameter :**Number of patches within a group $N^{(S)}$, number of groups for dictionary training $N^{(t)}$, number of training iterations $N^{(i)}$ and the size of dictionary *n x k*.
- **Dictionary learning stage :** Randomly choose $N^{(t)}$ groups to learn dictionary . Use the KSVD algorithm to train the dictionary by replacing the sparse coding stage with SSC problem.
- **SSC stage :** Perform the denoising on each group via SSC . Compute the final result $\widehat{\boldsymbol{Z}}^{(SSC)}$ by weighted averaging the filtering results of all groups.
- **Output : The filtering result $\widehat{\boldsymbol{Z}}^{(SSC)}$**

B. Refined Filtering

The aim of the refined filtering stage is to reduce the artifacts generated in the coarse filtering stage. Different transform domain filtering methods will produce different kinds of artifacts. The artifacts generated by sparse representation can be alleviated by other transform-domain filtering methods. Here choose wavelet packets to accomplish such task[1].

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Wavelet Packet Adaptive Thresholding

It consists of wavelet packet decomposition and owb extraction , thresholding the subbands and inverse wavelet packet transform. The algorithm is summarized in algorithm 1[12]. Here instead of instead of using a traditional wavelet transform for input image decomposition in mainstream literature, an OWB is employed.The threshold value is then picked up based on the statistical parameters of each subband coefficient. The optimal linear interpolation between each coefficient and the mean value of the corresponding subband are used to calculate the modified version of dominant coefficients[12].

Wavelet Packet and OWB

Wavelet packets originally known as optimal subband tree structuring is a discrete wavelet transform where discrete signal is passed through more filters than DWT. In the wavelet packet decomposition both detail and approximation coefficients are decomposed to create full binary tree and offers richest analysis.

In this type of transform, the optimal representation basis of the input signal is selected by optimizing a function known as “cost function” in each subband[12].The algorithm starts with computing the cost values from the deepest level nodes ie bottom up procedure. If the cost value of parent node is higher than the sum of cost value of 2 children nodes, then the children are retained, otherwise, they are discarded. This cost value computation process is recursively repeated up to the tree’s root. The result is a basis that has the cost having less among all the possible bases in this tree, so-called best basis or optimal basis [12].

Instead of this highly computational complex algorithm, fast method is introduced here for extracting OWB. The algorithm starts at the root and generates the optimal basis tree without growing the tree to full depth(top up procedure). In this algorithm, here use Shannon entropy to produce the optimal wavelet basis. The Shannon entropy of coefficients of subband S is calculated by [16]

$$SE(S) = -\sum_i S_i^2 \log (S_i^2) \qquad (15)$$

The output $\widehat{x_1}$ of coarse filtering is given to wavelet packet decomposition as input.The algorithm is summarized in Algorithm 4.

Threshold Value Determination and Thresholding Algorithm

An optimum threshold value, which is adaptable to each subband characteristics, is desired to maximize signal to noise ratio. In this algorithm, an adaptive threshold value λ_s for each subband S at level d is calculated as

$$\lambda_s = \alpha_{d,s}\left(\frac{\sigma_\eta^2}{\sigma_{I,s}}\right) \qquad (16)$$

where σ_η^2 and $\sigma_{X,s}$ are the variances of noise and clean image coefficients in the subband S, respectively. In the original algorithm, the term $\alpha_{d,s}$ was set to one, nevertheless, here employ this value for a larger threshold values for high-frequency subbands based on their level of decomposition and their corresponding subbands[12].

Here input noise varience is estimate dby applying the robust median estimator on the HH1 subband’s coefficients $\left(Y_{i,j}^{HH1}\right)$,

$$\hat{\sigma}_\eta^2 = \left[\frac{median\left(\left|\widehat{x1}_{i,j}^{HH1}\right|\right)}{0.6745}\right]^2 \qquad (17)$$

Also adapted equation (17) to estimate the image noise variance.

$$\sigma_{I,s}^2 = max\left(\sigma_{\widehat{x1},s}^2 - \sigma_\eta^2, 0\right) \qquad (18)$$

where $\sigma_{\widehat{x1},s}^2$ is the variance of coeffient $(\widehat{x1}_{i,j})$ in subband S.

A subband weighting function (SWF) in horizontal (SWF*H)* and vertical (SWF*V)* directions at level L of the WP decomposition is introduced. This function should be an increasing function on both directions.

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$$SWF_{H/V}(i) = \frac{i^2}{2^{2L}} \quad \text{for } i=1,2,\ldots\ldots\ldots.2^L \qquad (19)$$

where i is the index of subbands at the highest level of decomposition in horizontal and vertical directions, when decomposed subbands are matrixly arranged.The factor 2^{2L} is used to normalize the SWF, because in level L here have 2^L subbands in each direction. The SWF function is sampled at the midpoint of each subband at the highest decomposition level[12].

$$\alpha_{d,s} = \sum_{i\subset s} SWF_H(i) + \sum_{j\subset s} SWF_V(j) \qquad (20)$$

A new thresholding algorithm (OLI-Shrink) that uses optimal linear interpolation between each coefficient and corresponding subband mean in the modification of dominant coefficient[12].

$$\delta_{\lambda_S}^{OLI}(x1_{i,j}^S) = \begin{cases} 0, & |\widehat{x1}_{i,j}^S| \le \lambda_S \\ \widehat{x1}_{i,j}^S - \beta(\widehat{x1}_{i,j}^S - \mu_s) & |\widehat{x1}_{i,j}^S| > \lambda_S \end{cases} \qquad (21)$$

where μ_s is the mean value of the coefficient of subband s and β is computed by[12]

$$\beta \cong \frac{\sigma_\eta^2}{\sigma_{\widehat{x1},s}^2} \qquad (22)$$

ALGORITHM 4.4 : Fast OWB Extraction[12]

- Choose L as the maximum number of levels for WP decomposition.
- While the current level (d) of decomposition is less than L, for each existing subband (parent node) S_d^i ($0 \le i < 4d - 1$), do the following.

1) Compute the subband's Shannon entropy $SE(S_d^i)$ as the cost function.
2) Decompose S_d^i into 4 subbands (children nodes LL_{d+1}^{4i} , LH_{d+1}^{4i+1} , HL_{d+1}^{4i+2} and HH_{d+1}^{4i+3} and compute the Shannon entropy of them $SE(LL_{d+1}^{4i})$, $SE(LH_{d+1}^{4i+1})$, $SE(HL_{d+1}^{4i+2})$ and $SE(HH_{d+1}^{4i+3})$.
3) If $SE(S_d^i) < SE(LL_{d+1}^{4i}) + SE(LH_{d+1}^{4i+1}) + SE(HL_{d+1}^{4i+2}) + SE(HH_{d+1}^{4i+3})$, then only retain parent node and eliminate children nodes, otherwise retain parent and children node.
4) If there are no nodes to split, the process of extracting the OWB reaches the end.

IV.RESULTS AND DISCUSSION

Here use both simulated image and real SAR image to test the filtering performance of the proposed method shown in figure 2 and 3 respectively . A 256 x 256 test image , cameraman and one real SAR image ie 4-look AIRSAR image taken over Flevoland in Netherland.

Fig 2. Cameraman and flevoland image

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Free parameters used in the proposed method are listed in table 1

Table 1 Parameters used in the Proposed Method

Coarse filtering	n_1	C	$SL_1^{(p)}$	$N^{(S)}$	$N^{(t)}$	$N^{(i)}$	k
	64	17	1	8	2000	5	64

The filtering performance of cameraman is evaluated by the peak signal to noise ratio (PSNR) and structural similarity index (SSIM) . The PSNR and SSIM results for Cameraman are shown in table 2 .

Table 2 PSNR (dB) and SSIM results of cameraman

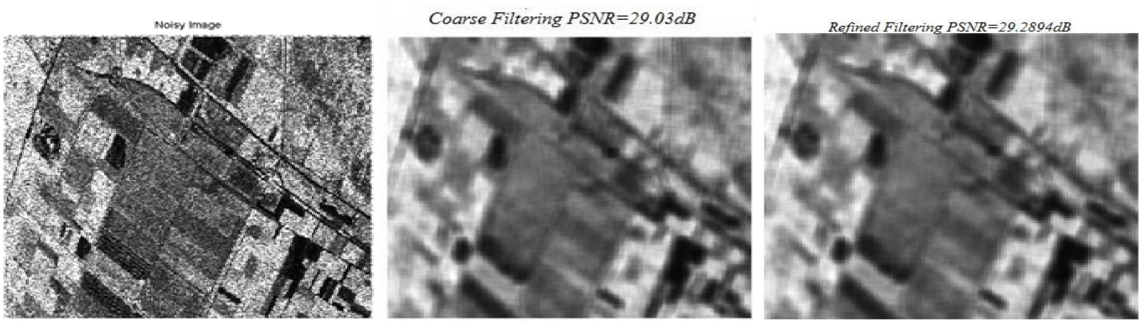
	PSNR		SSIM	
	Cameraman			
L	Coarse filtering	Refined filtering	Coarse filtering	Refined filtering
4	34.1986	34.2274	0.523	0.554
8	34.276	34.3103	0.575	0.600

With increase in L , filtering performance of the proposed method becomes better. The main reason of this behavior is that the learned dictionary which plays an important role in the proposed method becomes more and more suitable for SSC as L increases. The refined filtering stage removes most of the artifacts in the coarse filtering result .Thus the refined filtering stage is effective[1].

(a) (b) (c)

Fig 3. Filtered image of cameraman contaminated by 4 look speckle a) noisy image b) coarse filtering c) refined filtering

Fig 3 shows the filtered images for cameraman contaminated by 4 look speckle. Refined filtering removes the artifacts occurs as a result of simultaneous sparse coding.



(a) (b) (c)

Fig 4. Filtered image of flevoland contaminated by 4 look speckle a) noisy image b) coarse filtering c) refined filtering

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Fig.4 shows the filtered images for flevoland. PSNR of flevoland of coarse and refined filtering is 29.03 and 29.2894dB respectively. Another commonly used indicator for SAR image de-speckling is the ratio image [3] which represents the noise removed by SAR image de-speckling . The ratio image is defined as the point wise ratio between the original image *I* and filtered image .

$$r = \frac{I}{\hat{x}} \qquad (23)$$

The best result corresponds to the ratio image *r* which is the closest to the actual speckle *v*. Moreover, here also analyze the ratio image with the following quantitative indicators ,the mean of *r* . The mean of *r* are often used to indicate the bias [1]. Table 4 shows the mean of flevoland ratio image of proposed method.

Table 4. Mean of flevoland ratio image

Stage	Mean of r
Coarse filtering	0.969
Refined filtering	0.969

V. CONCLUSION

In this paper, a novel SAR image de-speckling method has been proposed. The homomorphic transformation was first applied and speckle filtering was implemented in the logarithmic domain. Then patch ordering algorithm is applied to order the patches . Then, a two-stage filtering strategy was proposed. In the coarse filtering stage, the ordered patches were filtered by learned SSC to effectively remove the noise. In the refined filtering stage, filtering is made by wavelet packets for removing the artefacts generated from the first stage. The final result was reconstructed by inverse wavelet packet transform.

Here used both simulated and real SAR images for validation of the proposed method. For simulated images, that the proposed achieves state-of-the-art performance in terms of PSNR and SSIM. For real SAR images, here used the mean of ratio image and PSNR to evaluate the filtering performance. The proposed method has strong speckle reduction ability .

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