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SAR Image Despeckling via Transform Domain Filtering

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***Abstract* - Processing of synthetic aperture radar (SAR) images has led to the development of SAR image despeckling approaches. These approaches help to suppress the Speckle in SAR Image. In this paper, we propose a Synthetic Aperture Radar (SAR) image despeckling method based on patch ordering and transform domain filtering. The proposed method consists of two-stage filtering strategy. The first stage is coarse filtering. In this stage, denoising is done by simultaneous Sparse Coding (SSC). The second stage is refined filtering which can eliminate small artifacts generated by the coarse filtering. In this stage, filtered image is obtained by Otsu Method. Experimental results with both denoised images and real SAR images demonstrate that the proposed method achieves state-of-art despeckling performance in terms of Structural Similarity Index Measure (SSIM), Peak Signal-to-Noise Ratio (PSNR), and Equivalent Number of Looks (ENL) and ratio image.**

Keywords — Despeckling, Simultaneous Sparse Coding (SSC), Otsu method, Synthetic AperatureRadar(SAR).

I. INTRODUCTION

As all coherent imaging systems, the synthetic aperture Radar (SAR) generates images that are severely degraded by a type of multiplicative noise denoted as speckle. Speckle is caused by random interference of the backscattered electromagnetic waves due to the roughness of the imaged surface. The presence of speckle affects the performance in many applications of SAR image processing. For example, it increases the false alarm rate in target/edge detection and decreases the correct classification rate in terrain classification[1]. Since speckle generally tends to obscure image details, reduction of the speckle noise is important in most detection and recognition systems.

Over the years, a variety of techniques has been developed to despeckle images. In general, the speckle in SAR images is characterized by the multiplicative noise model [3].

The purpose of despeckling is to recover the underlying target backscattering coefficient from the observed intensity image. To make this problem easier, the multiplicative model can be transformed into the additive model via homomorphic transformation[4], by taking the logarithm of the noisy image. Then, the image denoising methods developed for the additive noise case can be applied to the logarithmic SAR image, such as wavelet shrinkage, total variation, sparse representation and so on. In addition, the nonlocal means (NLM) algorithm proposed by Buades*et al.* provides a breakthrough in image denoising. This approach utilizes the similarity between the patches surrounding the estimated and the selected pixels to obtain the weight for pixel averaging in a large region. The NLM algorithm has also been extended to SAR and polarimetric SAR image despeckling. In particular, the probabilistic patch-based (PPB) algorithm replaces the Euclidean distance in by a statistical similarity criterion and achieves very good results in SAR image despeckling. Inspired by the block matching 3-D (BM3D) algorithm [30], Parrilli*et al.* proposed a SAR version of BM3D, i.e., SAR-BM3D, using local linear MMSE criterion and undecimated wavelet. Later, Cozzolino*et al.* proposed a fast adaptive nonlocal SAR (FANS) despeckling method based on SAR-BM3D. On the other hand, image denoising via sparse representation has also attracted an increasing amount of attention. Elad and Aharon proposed an image denoising method based on sparse representations over learned dictionaries which can be acquired by the K-SVD algorithm. Mairal*et al.* proposed the nonlocal sparse model for image denoising by combining the nonlocal method and simultaneous sparse coding (SSC). Most recently, the sparse model has been successfully applied to SAR image despeckling and found to be promising for multiplicative noise removal.

In this paper, we propose to address SAR despeckling in the transformed image domain via sparse representation. Similarly, we work on the logarithmic SAR images because of the reported better performance for the log-intensity data. However, our method is different from previous works in the following two aspects. First, we apply transform-domain filtering to the ordered SAR patches rather than the original image. we have designed a SAR-oriented patch ordering algorithm by the similarity measure based on SAR statistics. This procedure can effectively improve the signal regularity and hence enhance the performance of sparse representation. Second, we propose a two-stage strategy to both deal with speckle reduction and artifact elimination. Specifically, in the first stage (coarse filtering), the main purpose is to effectively remove the noise. Therefore, we filter the ordered patches with SSC because of their superior noise reduction ability combined. Then in the second stage, we apply patch ordering to the coarse filtering result again and process the ordered patches by Otsu method for refined filtering. Finally, the despeckled image is reconstructed from the refined result by inverse permutation and subimage averaging.

II. OBJECTIVES & OVERVIEW OF THE PROPOSED MECHANISM

In this paper, we propose a new SAR image Despeckling algorithm based on image filtering framework. Instead of applying spatial filtering to the ordered patches, we propose to use transform domain methods to fulfill this purpose. Moreover, the proposed algorithm consists of two stage. In the first stage, the log intensity SAR image is filtered by patch ordering and SSC. Although denoising via SSC can suppress speckle effectively, it produces small artifacts. Thus the first stage is the coarse filtering stage. The artifacts generated by sparse representation can be alleviated by another transform domain methods.

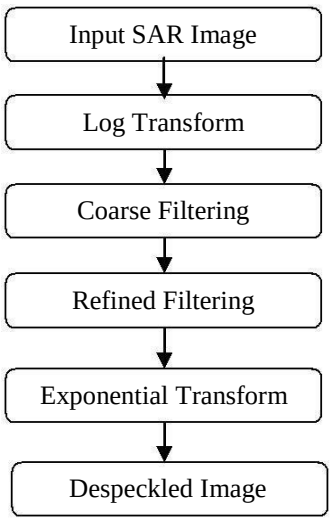

Figure 1. Flow diagram of the proposed method

To handle this, we adopt a refined filtering stage in which the coarse filtering result is filtered by patch ordering and Otsu thresholding.

A. Logarithmic Transformation

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

$$I = x.v$$

where I is the observed intensity (noisy image); x is the underlying target backscattering coefficient (noise-free image); and v is the speckle (multiplicative noise). After Logarithmic transformation,

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

The following filtering process will work on the log-intensity data.

B. Image Filtering Framework

In Coarse filtering, the patches are extracted from log transformed image and median filtered image. These patches are ordered based on similarity measure. Speckle is suppressed by Simultaneous Sparse Coding (SSC) denoising method, which is recently advanced in SAR image despeckling and the image is reconstructed by inverse permutation and subimage averaging.

In Refined Filtering, the patches are extracted from the Coarse filtering result and they are ordered in a same way as coarse filtering. In this stage, the artifacts are eliminated by Otsu thresholding . The image is reconstructed by inverse permutation and sub image averaging. ----------

Algorithm 1.The proposed algorithm for SAR image Despeckling

- - ***Input*:** The input SAR image I, the ENL L.

Step 1: Coarse filtering.

Median filtering.Apply a 3 × 3 median filter to input SAR image, and obtain the filtering result.

Logarithmic transformation. Calculate the log-intensity image by taking the logarithmic transformation with bias correction to original SAR image.

Patch extracting. Extract the sliding patches of $\sqrt{n} \times \sqrt{n}$ from filtered image and log transformed image respectively.

Patch ordering. Order the patches by Algorithm 2, and obtain the ordered set. Then calculate the ordered patches by permutation.

Denoising via SSC. Denoise the permuted image by Algorithm 3, and obtain the filtering result. Then perform inverse permutation on denoised image.

Subimage averaging. Reconstruct the filtering result from denoised image by subimage averaging.

Exponential transformation.Calculate the coarse filtering result by applying exponential transformation.

Step 2: Refined filtering.

Patch extracting. Extract the sliding patches from coarse filtering result and exponential transformed image, respectively.

Patch ordering. Order the patches and obtain the order set. Then perform permutation by the order.

Denoising via Otsu Method. Denoise the permuted image by Otsu thresholding, and obtain the filtering result. Then perform inverse permutation on the denoised image ***Subimage averaging.*** Reconstruct the filtering result from denoised image by subimage averaging.

Exponential transformation.Calculate the final filtering result by applying exponential transformation to the subimage averaged image.

***Output*:** The final filtering result x ----------

Let $\mathbf{y}_i$(i= 1, . . . , N(p)) be the column stacked version of these patches. The purpose of patch ordering is to reorder these patches in a smooth way. The original patch ordering algorithm utilizes the Euclidean distance as the similarity measurement. However, the Euclidean distance is not an appropriate choice for SAR images. Here we employ the block similarity measure (*BSM*) as the similarity measurement. The *BSM* of $\mathbf{y}_i$and $\mathbf{y}_l$is

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

We further take the following two measures to reduce the computation complexity of patch ordering. First, we drop the cycle-spinning method due to its high computational cost in exchange of only small performance improvement. Second, as suggested, we also restrict the search range to a $C \times C$ neighborhood surrounding the current patch. The detail of the simplified patch ordering algorithm for SAR images is shown in Algorithm 1.

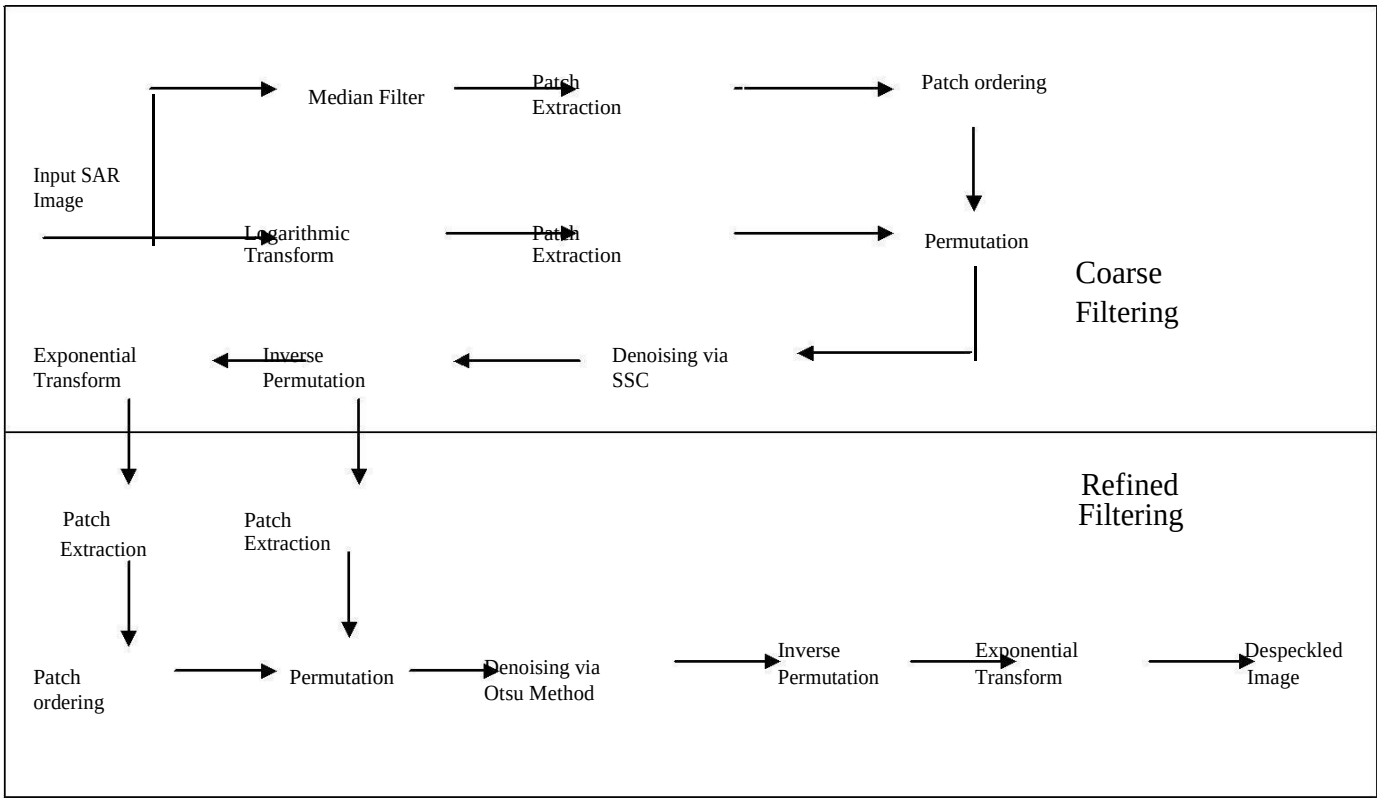

Figure 2. Complete flow of our proposed method

C. Patch Ordering for SAR Images

Suppose that the size of I is $N1 \times N2$.We extract the sliding patches of size $\sqrt{n}\times\sqrt{n}$ from I. If the sliding step is $SL(p)$, then the number of patches is

$$N(P) = \left\lfloor \frac{N1-\sqrt{n}}{SL(p)} + 1 \right\rfloor \left\lfloor \frac{N2-\sqrt{n}}{SL(p)} + 1 \right\rfloor$$

Algorithm 2.Simplified patch ordering algorithm for SAR Images

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***Input*:** The image patches $\mathbf{y}_i$(i= 1, . . . , N(p)).

Parameter: The search range $C \times C$.

Choose the first patch as the initial patch, i.e. $\Omega(1) = 1$. for i= 1 to $N(p)-1$ do

Let $\mathbf{y}\Omega(i)$ and Qi be the current patch and the set of indices of the search range around $\mathbf{y}\Omega(i)$, respectively. If $|Qi / \Omega| \geq 1$, then

Qi / Ω.

Choose the patch y] corresponding to the smallest *BSM*. else
end if
$\Omega(i+1) = l$
end for
***Output*:** The set Ω which holds the ordering. ----------

Suppose that **Y** and **Z** are the patches before and after patch ordering, respectively,

$\mathbf{Y} = [\mathbf{y}1.....\mathbf{y}N(P)]$

$\mathbf{Z} = [\mathbf{z}1..... \mathbf{z}N(P)]$.

$\mathbf{Z} = \mathbf{Y}\mathbf{P}\Omega$

where $\mathbf{P}\Omega$ is the $N(p) \times N(p)$ permutation matrix corresponding to the set Ω which holds the ordering.

D. Denoising via SSC

Algorithm 3. Denoising Via SSC

***Input*:** The ordered patches **Z**, the ENL *L*.
Parameter: The number of patches within a group $N(S)$, the number of groups for dictionary training $N(t)$, the number of training iterations $N(i)$, the size of dictionary $n \times k$.
***Dictionary learning stage*:** Randomly choose $N(t)$ groups for dictionary learning.
***SSC stage*:** Perform the denoising on each group via SSC. Compute the final result $\mathbf{Z}(SSC)$ by weighted averaging the filtering results of all groups.
***Output*:** The filtering result $\mathbf{Z}(SSC)$. ----------

E. Denoising via Otsu thresholding

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 we choose thresholding method to accomplish such task. We apply patch ordering to $x1$ and obtain the set Ω. Let $\mathbf{Y2}$ be the patches extracted from the logarithm of $x1$. Then, the ordered patches $\mathbf{Z2}$ can be obtained by $\mathbf{Z2} = \mathbf{Y2}\ \mathbf{P}\Omega$. Finally, The despeckled image is obtained by taking exponential transformation to the refined filtering result.

III. RESULTS AND DISCUSSION

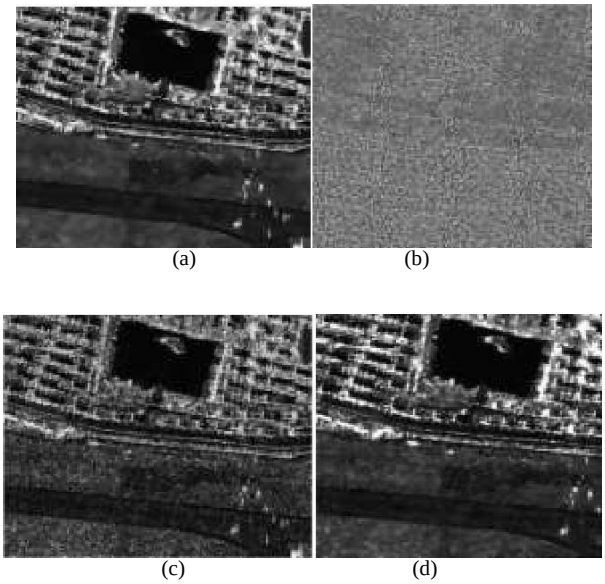

Figure 1. (a) Original image. (b) Patch ordered image(c) Coarse filtered image (d) Refined filtered image

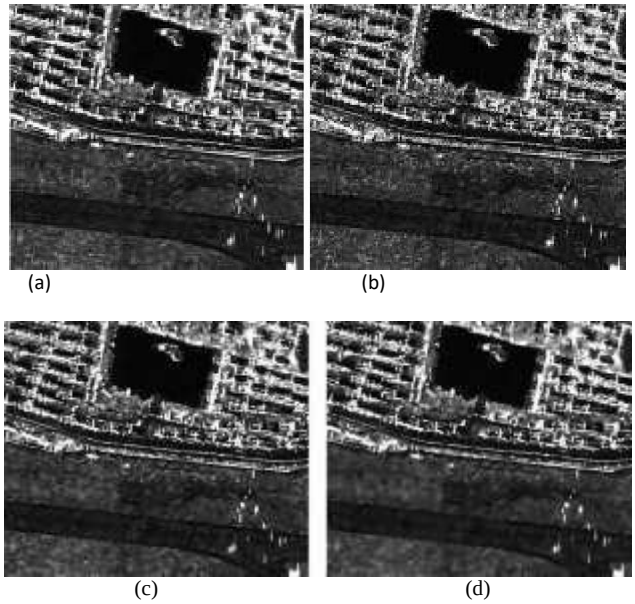

Figure 2.Filtered images (a) PPB (b) SAR BM3D (c) Coarse filter (d) Refined filter

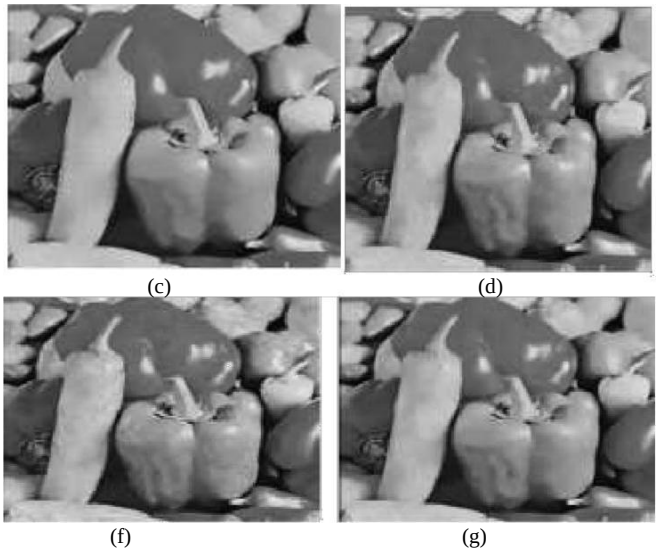

Figure 3(a)Original image (b) Noisy image. (c) PPB (d) SAR BM3D (e) Coarse filtered image (f) Refined filtered image

Table 1 PSNR Results for Peppers and Cameraman

	Peppers	Cameraman
Noisy	23.67	23.67
PPB	29.86	28.89
SAR – BM3D	31.37	31.40
Coarse filtering	31.62	31.14
Refined filtering	31.33	31.63

Table 2 SSIM Results for peppers and Cameraman

	Peppers	Cameraman
Noisy	0.543	0.561
PPB	0.865	0.861
SAR – BM3D	0.897	0.906
Coarse filtering	0.883	0.889
Refined filtering	0.901	0.899

Table 3 ENL Results for Dalian

	Dalian
Noisy	1.00
PPB	47.98
SAR – BM3D	8.39
Coarse filtering	26.47
Refined filtering	46.27

IV. CONCLUSION

In this paper, a novel SAR image despeckling method has been proposed. The homomorphic transformation was firstapplied and speckle filtering was implemented in the logarithmic domain. Specifically, the patch ordering method originally developed for additive white Gaussian noise was adapted to SAR images. Then, a two-stage filtering strategy was proposed. In the coarse filtering stage, the ordered patches of the logarithmic SAR image were filtered by SSC. In the refined filtering stage, the ordered patches of the coarse filtering result were further filtered by Otsuthresholding. The final result was reconstructed from the refined filtering result by inverse permutation, subimage averaging, and exponential transformation.

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