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SAR IMAGE DESPECKLING USING PATCH ORDERING AND TRANSFORM DOMAIN FILTERING

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Abstract: In this paper, proposes a synthetic aperture radar (SAR) image despeckling method based on patch ordering and transform-domain filtering. Logarithmic transformation with bias correction is applied to the original SAR image to transform the multiplicative noise model into the additive model. Then, adopts a two-stage filtering strategy. The first stage is coarse filtering which can suppress speckle effectively. In this stage, we extract the sliding patches from the logarithmic SAR image, and order them in a smooth way by a simplified patch ordering algorithm specially for SAR images. The ordered patches are filtered by learned simultaneous sparse coding (SSC), a technology recently advanced in image processing. Then, the 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 artifacts generated by the coarse filtering. In this stage, the sliding patches are extracted from the coarse filtering result and ordered in the same way. Then, apply 2-D wavelet hard thresholding to the ordered patches and reconstruct the refined filtering result. The final result is obtained by taking exponential transformation to the refined filtering result.

Key words: Despeckling, patch ordering,simultaneous sparse coding (SSC), synthetic aperture radars (SAR).

I. INTRODUCTION

SYNTHETIC aperture radar (SAR) images , acquired via coherent imaging, are intrinsically associated with a noise-like phenomenon called speckle. 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 rate in terrain classification. Thus, SAR image despeckling is an important pre-processing step and many methods have been proposed during the past three decades. In general, the speckle in SAR images is characterized by the multiplicativenoise model. 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 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. Another commonly used approach is to write the multiplicative noise in an additive but signal dependent way. Many classical despeckling techniques adopt this model and perform filtering in the spatial domain based on the minimum mean square error (MMSE) criterion or the maximum a posteriori (MAP) criterion. Some advanced methods also adopt the additive signal dependent model, but operate in the wavelet domain or non subsampledshearlet transform domain. In addition, the nonlocal means (NLM) algorithm proposed by Buades. 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 based on the Nakagami–Rayleigh distribution and achieves very good results in SAR image despeckling. Inspired by the block matching 3-D (BM3D) algorithm, Parrilli. Proposed a SAR version of BM3D, i.e., SAR-BM3D, using local linear MMSE criterion and undecimated wavelet. Later, Cozzolinoproposed 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 dictionarieswhich can be acquired by the K-SVD algorithm .Mairalet 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, also propose to address SAR despeckling in the transformed image domain via sparse representation. Similarly, work on the logarithmic SAR images because of the reported better performance for the log-intensity data. However, method is different from previous works in the following two aspects. First, apply transform-domain filtering to the ordered SAR patches rather than the original image. In particular, inspired by the work of Ram, 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 2-D wavelet for refined filtering. Finally, the despeckled image is reconstructed from the refined result by inverse permutation and subimage averaging. It is worth mentioning that our motivation to propose the aforementioned two-stage algorithm in fact stems from the well-known observation that any single-stage transform domain is susceptible to produce artifacts. This phenomenon is especially significant when the signal-to-noise ratio (SNR) becomes worse as that in SAR imagery. The solution proposed here is then to exploit different transformation bases, which is based on the intuitive idea that independent transform-domain filtering methods will often produce complementary artifacts. For example, it is very likely that the learned dictionary by K-SVD and the wavelet basis, one being image dependent and one generic, are responsible for spurious artifacts at different places. Since most of these artifacts appear like high-frequency noisy components, applying the second stage of filtering will effectively remove those artifacts associated with the first stage. Importantly, although the second stage of filtering may still produce new artifacts (ringing effects if using wavelets), it is important to notice that the sole purpose at the second stage is to remove a small number of isolated artifacts rather than the ubiquitous noise (task already accomplished by the first stage). Thus, we are actually allowed to use a rather conservative value for thresholding wavelet coefficients, which can efficiently suppress the artifacts from the first stage and at the same time avoid secondary ones that might ensue.

II. LITERATURE SURVEY

A. Unsupervised speckle level estimation of SAR images

Assumed that fully developed speckle intensity has a Gamma distribution. Based on this assumption, estimation of the equivalent number of looks (ENL) is transformed intonoise variance estimation in the logarithmic SAR image domain. In order to improve estimation accuracy, texture analysis is also applied to exclude areas where speckle is not fully developed (e.g., urban areas). Finally, the noise variance is estimated by a 2-dimensional autoregressive (AR) model. The effectiveness of this method is verified with several SAR images from different SAR systems and simulated images. This method was validated with real SAR images from different systems and simulated images. Experimental results showed that the combined approach of texture analysis and AR model can effectively improve the accuracy of unsupervised ENL estimation. In addition, the computational time of this method was also found acceptable for practical applications. Noise variance estimation using:

1) Texture Analysis:Since the ENL is related to the Gamma distribution noise model which is only applicable for fully developed speckle,the presence of highly textured areas will cause significant ENL underestimation. So such areas should be excluded for ENL estimation. The textural information is very rich in urban areas and poor in flat areas. Since textural features can be used for image classification, we analyze the textural information in SAR images and select flat regions where speckle is fully developed to estimate the speckle level.

2) AR Model:The AR model is a very simple and effective method as is well established in the modern spectral estimation theory. Now the remaining problem is the estimation of noise variance in the logarithmic SAR image for the $K \times K$ blocks selected by texture analysis.

III. PROPOSED SYSTEM

A. Logarithmic SAR image statistics and patch ordering

Here,two important preprocessing steps are used. Since performs filtering on the log-intensity data, first review the logarithmic SAR statistics from which we can obtain the mean and variance of the log-transformed speckle. This information will be fed to algorithm for bias removal and setting of filtering parameters. Second, describes the image filtering framework of patch ordering that precedes each step of transform-domain filtering. Particularly, a new patch ordering algorithm that adapts to the nature of SAR data and furthermore take two simplifying measures in order to reduce the computation complexity.

1) *Logarithmic SAR image statistics*: In SAR images, the speckle is characterized by the multiplicative noise model.

$I = xv$

whereI is the observed intensity (noisy image); x is the underlying target backscattering coefficient (noise-free image); and v is the speckle (multiplicative noise). It is well established that fully developed speckle follows the Gamma distribution.

$$p_v(v) = \frac{L^L v^{L-1}}{\Gamma(L)} \exp(-vL), v \geq 0$$

whereL is the equivalent number of looks (ENLs) and $\Gamma(\ )$ is the Gamma function. The ENL can be effectively obtained by supervised or unsupervised estimation. For ahomogeneous region, the ENL can be calculated by

$$L = \frac{(\text{mean}\ )2}{\text{var}}$$

Thus, the ENL is treated as a known parameter. By logarithmic transformation of I, the multiplicative noise becomes additive, i.e

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

The mean and variance of ln(v) are related to the ENL by

$$E[\ln(v)] = \psi^{(0)}(L) - \ln(L)$$

$$\text{var}[\ln(v)] = \psi^{(1)}(L)$$

where$\psi^{(m)}(L)$ is the polygamma function of order m. Then the log-intensity SAR image with bias correction is

$$I^{(\ln)} = \ln(I) - \psi^{(0)}(L) + \ln(L).$$

2) Image filtering framework of patch ordering: The original image filtering framework of patch ordering is shown in Fig.1. In general, the sliding patches extracted from the input image are first ordered and permuted. Then, these ordered patches are filtered. The final result can be reconstructed from the filtered patches via inverse permutation and subimage averaging.

Specifically for filtering SAR images, the patch ordering framework needs to be adapted. Because of working on the log-intensity data, thepatches are extracted from the logarithmically transformed SAR image. Nevertheless, ordering and permutation of these patches will still be implemented based on their similarity from the original (amplitude) SAR image.

3)Patch ordering for SAR images: Suppose that the size of I is $N_1 \times N_2$.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

$$N^{(p)} = \left\lceil \frac{N_1 - \sqrt{n}}{SL^{(p)}} \right\rceil + 1 \left\lceil \frac{N_2 - \sqrt{n}}{SL^{(p)}} \right\rceil + 1$$

where$\lceil . \rceil$is the ceil function.

Let yi(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.

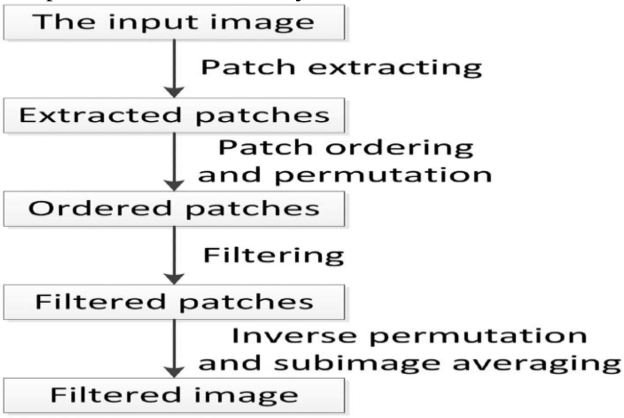


Fig.1. Image filtering framework of patch ordering.

The original patch ordering algorithm utilizes the Euclidean distance as the similarity measurement. In addition, it has randomness in order to facilitate the cycle-spinning method. 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 $y_i$and $y_l$is

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

Further take the following two measures to reduce the computation complexity of patch ordering. First, drop the cycle-spinning method due to its high computational cost in exchange of only small performance improvement. Second, also restrict the search range to a $C \times C$neighbourhood surrounding the current patch.

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

$$Y = [y_1 \cdot \cdot \cdot y_{N(p)}]$$
$$Z = [z_1 \cdot \cdot \cdot z_{N(P)}]$$

Then we have

$$Z = YP_\Omega$$

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

IV. ALGORITHM

In this paper, a new SAR image despeckling algorithm based on the image filtering framework shown in Fig.1. Instead of applying spatial filtering, to the ordered patches, we use transform domain methods, i.e., sparse representation and wavelet to fulfil this purpose. Moreover, the proposed algorithm consists of two stages. 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 which are caused by the learned dictionary. Thus the first stage is a coarse filtering stage.

Theartifacts generated by sparse representation can be alleviated by other transform domain methods. To handle this, we adopt a refined filtering stage in which the coarse filtering result is filtered by patch ordering and 2-D wavelet hard-thresholding. The complete procedure is hierarchically illustrated in Fig. 2.

A. Simplified patch ordering algorithm

Input: The image patches y_i(i= 1, . . . , $N^{(p)}$).
Parameter: The search range C × C.
Choose the first patch as the initial patch, i.e. Ω(1) = 1. For i= 1 to$N^{(p)}-1$ do
Let $y_{\Omega(i)}$and $Q_i$be the current patch and the set of indices of the search range around $y_{\Omega(i)}$, respectively.
if|Qi\Ω| ≥ 1', then
Calculate the BSM of $y_l$and $y_{\Omega i}$, where l ∈Qi\Ω. Choose the patch $\hat{y'}_l$corresponding to the smallestBSM.
else
Choose the spatially nearest patch $\hat{y_l}$to y_l
end if
Ω(i+ 1) = $\hat{l}$
end for
Output: The set Ω which holds the ordering.

B. SAR image despeckling algorithm

Input: The input SAR image I, the ENL L.
Step 1: Coarse filtering.
Boxcar filtering: Apply a 3 × 3 Boxcar filter to I, and obtain the filtering result I_B.

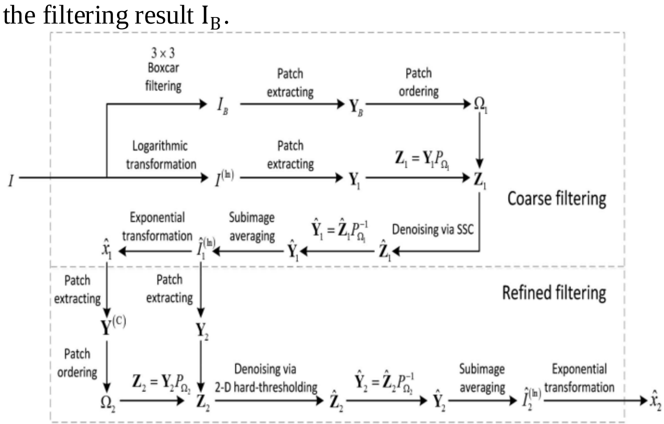


Fig. 2. Flowchart of the proposed algorithm.

Logarithmic transformation with bias correction: Calculate the log-intensity image $I^{(ln)}$by taking the logarithmic transformation with bias correction to I.

Patch extracting: Extract the sliding patches $Y_B$and $Y_1$of size $\sqrt{n_1}\times\sqrt{n_1}$from $I_B$and ,$I^{(ln)}$respectively.

Patch ordering: Order the patches $Y_B$by Algorithm 1, and obtain the set Ω_1. Then calculate the ordered patches Z_1 by

$$Z_1 = Y_1 P_{\Omega_1}$$

Denoising via SSC: Denoise Z_1 and obtain the filtering result $\hat{Z}_1$. Then perform inverse permutation on $\hat{Z}_1$, ie $\hat{Y}_1 = \hat{Z}_1 P_{\Omega 1}^{-1}$

Sub-image averaging: Reconstruct the filtering result $\hat{I}^{(\ln)}$ from $\hat{Y}_1$ by sub-image averaging .

Exponential transformation: Calculate the coarse filtering result $\hat{x}_1$ by applying exponential transformation to $\hat{I}^{(\ln)}$.

Step 2: Refined filtering.

Patch extracting: Extract the sliding patches $Y^{(C)}$ and Y_2 of size $\sqrt{n_2} \times \sqrt{n_2}$ from $\hat{x}_1$ and $\hat{I}_1^{(\ln)}$, respectively.

Patch ordering: Order the patches $Y^{(C)}$, and obtain the set Ω_2. Then calculate the ordered patches Z_2 by $Z_2 = Y_2 P_{\Omega 2}$

Denoising via 2-D wavelet hard-thresholding: Denoise Z_2 by 2-D wavelet hard thresholding, and obtain the filtering result $\hat{Z}_2$. Then perform inverse permutation on $\hat{Z}_2$, i.e. $\hat{Y}_2 = \hat{Z}_2 P_{\Omega 2}^{-1}$

Sub-image averaging: Reconstruct the filtering result $\hat{I}_1^{(\ln)}$ from $\hat{Y}_2$ by subimage averaging.

Exponential transformation: Calculate the final filtering result $\hat{x}_2$ by applying exponential transformation to $\hat{I}_2^{(\ln)}$.

Output: The final filtering result $\hat{x}_2$.

C. 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. Use the KSVD algorithm to train the dictionary by replacing the sparse coding stage in with the SSC problem.

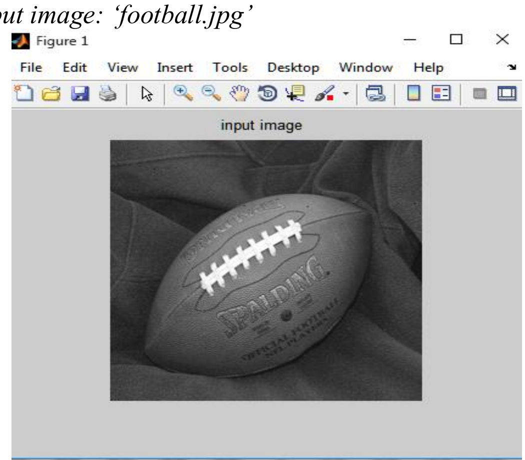
SSC stage: Perform the denoising on each group via SSC. Compute the final result $Z^{(SSC)}$ by weighted averaging the filtering results of all groups.

Output: The filtering result $Z^{(SSC)}$.

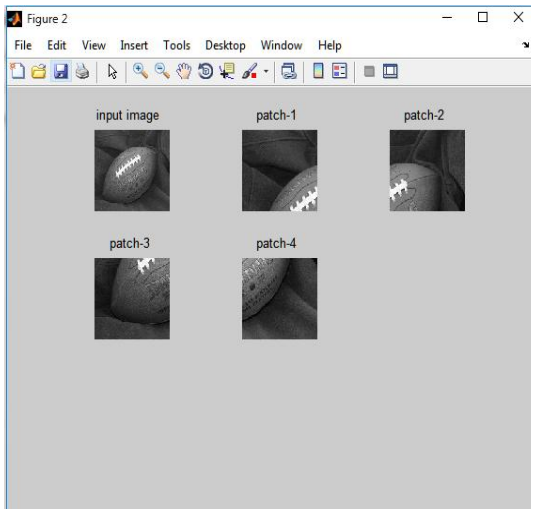
V. SIMULATION RESULTS

The simulation results are as follows:

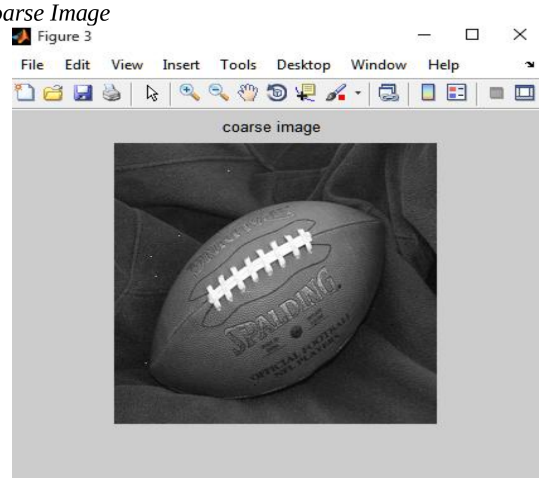
1) Input image: 'football.jpg'



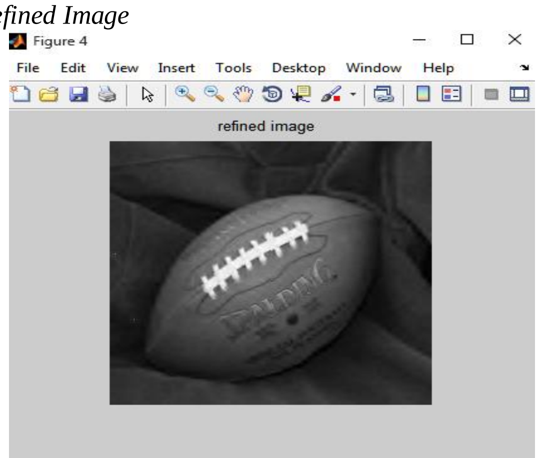
2) Patch Extraction



3) Coarse Image



4) Refined Image



VI. CONCLUSION

In this paper, a novel SAR image despeckling method has been proposed. The homomorphic transformation was first applied 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 learned SSC. In the refined filtering stage, the ordered patches of the coarse filtering result were further filtered by 2-D wavelet hard-thresholding. The final result was reconstructed from the refined filtering result by inverse permutation, sub image averaging, and exponential transformation. Future work will focus on the following three aspects. First, the proposed method can be improved especially in 1-look case by improving the efficiency of dictionary learning which is also a challenging problem in sparse representation. Second, fast algorithm of the proposed method should be developed. Third, the proposed method will be extended to polarimetric SAR despeckling which is also a hot topic in SAR image processing

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