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SAR Image De-Noising based on GNL-Means with Optimized Pixel-Wise Weighting in Non-Subsample Shearlet Domain

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Abstract

SAR images have been widely used in many fields such as military and remote sensing. So the suppression of the speckle has been an important research issues. To improve the visual effect of non-local means, generalized non-local (GNL) means with optimized pixel-wise weighting is applied to shrink the coefficients of non-subsample Shearlet transform (NSST) of SAR image. The new method can optimize the weight of GNL, which not only improve the PSNR of de-noised image, but also can significantly enhance the visual effect of de-noising image.

Keywords: SAR image de-noising, NSST, GNL, optimized pixel-wise weighting

1. Introduction

Normally SAR image de-noising methods can be classified into two types (Goodman, 2001). One is de-noised methods based on spatial filtering, and the other is de-noised methods based on multi-scale transform. For example, Lee filter (Lee et al, 1994), total variation regularization de-noising methods (Eom, 2011) and non-local means (NLM) de-noising methods (Torres, 2013) are de-noised methods base on spatial filtering; Bayesian wavelet shrinkage with edge detection for SAR image despeckling (Dai et al, 2004), and the SAR image despeckling based on nonsubsampled shearlet transform (Hou et al, 2012) are de-noised methods based on transform domain. In recent years, with the continuous improvement of the theory of multi-scale and multi-resolution transform, the de-noised methods based on transform domain are widely used in SAR image de-noising. For traditional Wavelet lack selectivity and is not sparse in the high-dimensional space. In order to improve the limitation of traditional Wavelet, many multi-scale multi-resolution transforms have been proposed. Recently, Contourlet (Do et al, 2002), Curvelet (Candès et al, 2004; Liu et al, 2014) and Shearlet (Lim, 2010) are the most widely used in image processing. Among these transforms, Curvelet is not produced based on a single function, and the construction of Contourlet can not be accord with multi-resolution analysis (MRA). So, from a brief and strict mathematical framework, Shearlet is proposed to overcome the disadvantages of Curvelet and Contourlet. In our paper, the construction of NSST in Lim (2010) is used to remove the speckle of SAR images.

So far, many methods have been proposed to remove noise of natural image. Non-local image de-nosing method proposed by Buades is a major breakthrough in the de-noised methods based on spatial filtering (Buades et al, 2005). In non-local means (NLM), by making use the repeat patterns existed in natural images (Buades et al, 2005), the gray pixel value is computed by all similar images in the weighted average between a fixed window centered on it and the windows centered on the other pixels in the whole image. By improving collaborative filtering and the compution of de-noised weight, in Dai et al. (2004) and Hou et al. (2012), non-local mean is extended to SAR image de-noising filed. NLM filter maked use of spatial correlation of the whole image to remove noise and can gain satisfactory results. However, NLM filter can not suppress any noise from not repeating neighborhoods. So, by combining the advantages of Wavelet and NML, in Dabov et al. (2007), block method of 3-Dimension (BM3D) is constructed, which can improve the performance of the NML well. Then, BM3D is extended to speckle suppression method in Parrilli et al. (2012), which is one of the important SAR image de-noising methods. The homomorphic transform is used to covert speckle to Gaussian noise in Dabov et al. (2007) and Parrilli et al. (2012) because that NL-means cannot be directly applied to speckle suppression, and which will produce some man-made ripple in the de-noised image. To improve the above disadvantage, in Luo et al. (2012), the authors proposed generalized non-local means (GNL-means) to deal with non-identically distributed image noise. Experiments show that GNL-means gain almost the same noise reduce effect to BM3D, and does better work than NL-means. In Liu et al. (2015), GNL-means is extended to speckle suppression by combining non-subsample Shearlet domain to gain a better de-noising performance. The calculations of weighting always suppose that the clear pixel estimates as independent random variables, which is not accord with the facts. In Feng et al. (2015), the authors analyze the correlation among the estimates and propose a bias-variance model to estimate the mean squared error (MSE) under various weights. The new model exploits the overlapping information of the patches by utilizing the optimization to try to minimize the estimated MSE. Under this model, a new weighting approach is proposed based on quadratic programming (QP). So, in our paper, a new de-noised method based on GNL-means with optimized pixel-wise weighting in NSST domain is proposed to suppress the speckle. The same to Feng et al. (2015), we use QP to compute the weight of GNL means, which can directly suppress the SAR image noise, and also can achieve a better de-noising performance.

The content of our paper can be summarized as follows. In Section 2, the SAR image de-noising method by GNL-means based on NSST is introduced. And we express how to take use of the overlapping information of the patches to optimize the weight of GNL-means. In Section 3, some experiments are made to show that the performance of our method. Some conclusions are drawed in Section 4.

2. Methods

2.1 Non-Subsample Shearlet

NSST in Lim (2010) has two phases: multi-scale decomposition and multi-orientation decomposition. Multi-scale decomposition can be constructed by Non-subsampled pyramid. By multi-scale decomposition, the *k*-th scale low frequency coefficients can be decomposed to *k*+1 sub-bands that contains one low frequency band and *k* high frequency bands whose sizes are all the same as the source image. The multi-orientation decomposition can be constructed by improved shearing filters by making the standard shearing filter map from pseudo-polar coordinate systems into Cartesian system to satisfy the property of shift-invariance (Lim, 2010). Image de-noising based on NSST can both remove the noise heavily and retain the texture of the original image well (Lim, 2010).

2.2 GNL-Means

Clean pixels value in NL-means can be gained the by weighting similar pixels average, and the weights is an exponential decreasing function as the similarities decrease. Let U_i and V_i be the noise-free and noise pixel value. Then, the noise model can be expressed by $Z_i = U_i + V_i$, where *i* can range in value from 1 to *M*, (*M* is the total number of pixels of the image). So, the estimates of U_i should be calculated as following.

$$\hat{Z}_i = \frac{1}{C} \sum_{j \in N_i} W_{ij} Z_j \tag{1}$$

where N_i denotes the search window which centered at pixel i. W_{ij} represents the weight of similar pixels, and $C = \sum_{j \in N_i} W_{ij}$ denotes a normalization term. W_{ij} can be calculated by Euclidean distance between Z_i and Z_j.

To modify NL-means to deal with non-i.i.d. noises, a two-stage noise suppression method by iterating NL-means is proposed in Luo et al. (2012). In this method, the weight is calculated by using patch-based squared Euclidean distance. $Z_i(k)$ denotes the pixels fall in patches around at the center of the *i*-th pixel, while $Z_j(k)$ denotes the pixels fall in patches around at the center of the *j*-th pixel. *d* is the number of pixels in a patch. Let us suppose each couple of pixels $Z_i(k)$ and $Z_j(k)$ is independent Gaussian. Let:

$$\Delta_{ij}(k) \overset{def}{=} Z_i(k) - Z_j(k) \tag{2}$$

Then we can know that $\Delta_{ij}(k)$ is also correspondent to normal distribution and the variance of $\Delta_{ij}(k)$ is $2\sigma^2$.

Then, the distance of each patch can be computed as follows.

$$D_{patch}(Z_i, Z_j) \overset{def}{=} 2\sigma^2 \sum_{k=1}^{d} [\Delta_{ij}(k)^2 / Var(\Delta_{ij}(k)) - 1] \tag{3}$$

Then, the weight can be extended to a generalized weight in NL-means:

$$W_{ij}^{G} \overset{def}{=} \exp\left(-\frac{1}{dT^2/2} \max\left\{ \sum_{k=1}^{d} \left[\frac{\Delta_{ij}(k)^2}{Var(\Delta_{ij}(k))} - 1 \right], 0 \right\} \right) \tag{4}$$

From (3) and (4), we can know that NL-means can be generalized by replacing W_{ij} with W_{ij}^{G}. So, the new NL-means is called Generalized NL-means (GNL-means). In patch wise NL-means, we use the patches instead of pixels to calculate weights, and simultaneously de-noise all pixels within the same patch. The number of patches that cover it is the number of estimates for each pixel. We can get the final de-noised value by averaging of all these estimates.

2.3 SAR Image De-Noising based on GNL-Means in NSST Domain

As generally, in SAR images, the speckle is fully developed (Good, 1976), so the noise model of SAR image de-noising can represented as follows.

$$I = R * F \tag{5}$$

where I indicates SAR image which contaminated by noise. R denotes the real landscape scenes (noise-free image). F indicates speckle process noise. Logarithmic transform is applied to two sides of (5) to convert speckle to Gaussian noise, as (6) shows:

$$\log(F) = \log(R) + \log(N) \tag{6}$$

where $\log(N)$ fits Gaussian distribution without identical. Form Liu et al. (2015), we can know that the high-bands coefficients of NSST of the image with Gaussian are also fit Gaussian distribution. So, GNL-means can be used to suppress the noise in high-bands of NSST, which can remove artificial texture effectively. The de-noising steps can be described as following.

1) Firstly, apply logarithmic transform to the original image. From this operation, multiplicative noise is converted to Gaussian noise.

2) Apply NSST to speckle image, and apply GNL-means to high-bands coefficients of NSST.

3) Noise free SAR image can be reconstructed through invert NSST.

4) Finally, final de-noising image is got by exponential operator.

2.4 Generalized Non-Local Means with Optimized Pixel-Wise Weighting

Non-local similarity model are still somewhat simpler, either using simple averaging or independent derivation of the weights based on certain transform coefficients of the corresponding image patches themselves. If the weighting estimates are independent random variables, we will obtain the optimal weighting method. However, under the assumption of independence, the estimates are impossible to be heavily correlated due to overlapping of the patches. So, by analyzing the correlation among the estimates, the authors improve the de-noising performance based on the overlapping patches information. Firstly, they optimize the weight under bias-variance model of minimum MSE with the help of the overlapping information. And then, under the bias-variance model, they use QP to solve the optimization problem.

GNL-means is also patches based de-noising method. So, with the help of the overlapping information, we can also optimize the weight under bias-variance model of minimum MSE. To simple the calculation, we convert GNL-means to the follow equation:

$$\hat{Z}_i = \sum_{j \in N_i} \omega_{ij} Z_j \tag{7}$$

where $\omega_{ij} = W_{ij}^G / C$ denotes the weights. Denote $P_i = (p_{i,1}, ..., p_{i,N_i})$, $c_i = (c_{i,1}, ..., c_{i,N_i})^T$ and $\omega_i = (\omega_{i1}, ..., \omega_{iN_j})^T$, and (7) can be represented by (8):

$$\hat{Z}_i = \omega_i^T (P_i^T Z_j + c_i) \tag{8}$$

That means the objective function can be represented by follows:

$$f(\omega) = M \bullet \mathrm{E}[MSE(\hat{Z}_i(\omega))] = \hat{Z}_i = \sum_{j \in N_i} \omega_i^T (Q_i + \sigma^2 P_i^T P) \omega_i \tag{9}$$

Where $Q_i = (Z_i \mathbf{1} - P_i^T Z - c_i)(Z_i \mathbf{1} - P_i^T Z - c_i)^T$.

So, under the bias-variance model, we use QP to solve the optimization problem based on the method in Feng et al. (2015). The GNL-means with optimized pixel-wise weighting called GNL-OPWW. In our paper, we use GNL-OPWW to replace GNL-means in the speckle suppressed model by GNL-means in NSST domain to de-noise SAR image. The new de-noising steps can be described as following.

1) Firstly, apply logarithmic transform to the original image. From this operation, multiplicative noise is converted to Gaussian noise.

2) Apply NSST to speckle image, and apply GNL-means to high-bands coefficients of NSST.

3) Under the bias-variance model, QP is applied to solve the optimization problem to gain the best pixel-wise weighting. And use this weight to improve the performance of GNL-means in high-bands coefficients of NSST.

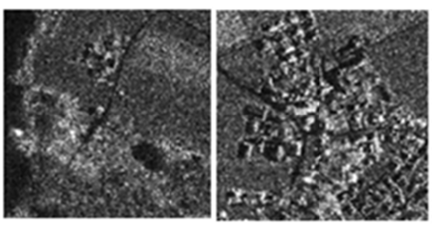
4) Noise free SAR image can be reconstructed through invert NSST.

5) Finally, final de-noising image is got by exponential operator.

3. Results

In this paper, the compared methods are as follows: Image de-noising based on NSST (NSST) (Hou et al, 2012), nonlocal SAR image de-noising based on LLMMSE (NL-LMSE) (Parrilli et al, 2012), GNL-means de-noising (GNL) (Luo et al, 2012), de-noising based on GNL-means in NSST domain (GNL-NSST) (Liu et al, 2015) and Bayesian Shearlet shrinkage de-noising via spare representation (BSSR) (Liu et al, 2014). Comparing the proposed algorithm (GNL-OPWW-NSST) with the mentioned algorithms, it is meaningful to prove the reliability and validity of the proposed algorithm.

The test images are different SAR scenes images which are shot by TerraSAR-X of the European Space Agency. Fig.1 shows the test SAR images.



(a) (b)

Figure 1. The real SAR image: (a) The SAR image of fields (b) The SAR image of woods

Then, Fig.1 (a) and (b) are SAR image of a field and woods. Apply the mentioned de-noising methods to the test images in Fig. 1. The de-noised images of these methods are shown in Fig. 2.

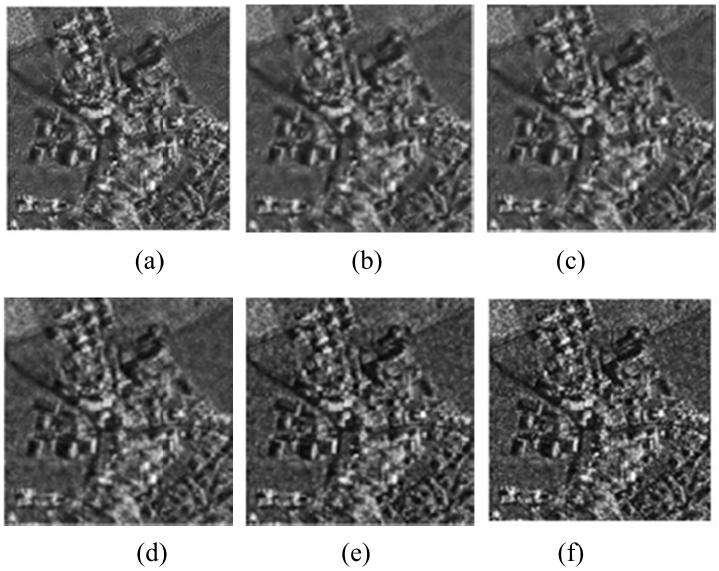


Figure 2. The de-noising fields SAR image by all de-noised method (a) De-noising by NSST (b) De-noising by NL-LMSE (c) De-noising by GNL (d) De-noising by GNL-NSST(e) De-noising by BSSR (f)De-noising by ours

Fig. 3 shows the de-noised woods SAR image by these methods.

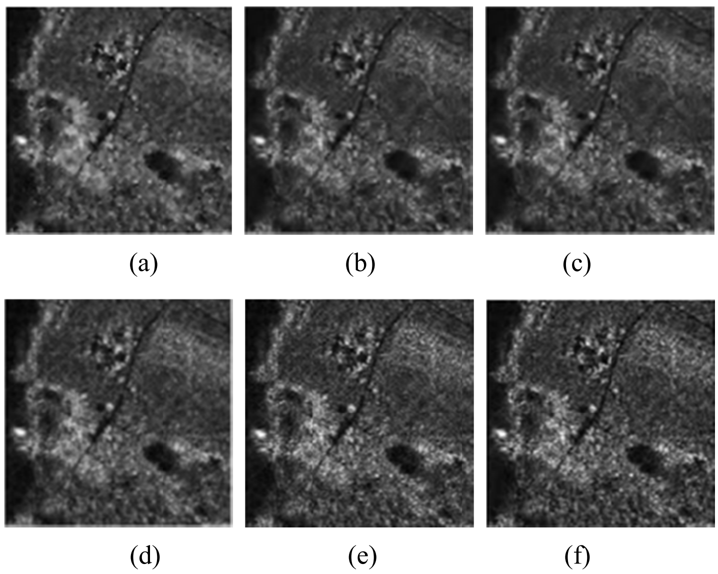


Figure 3. The de-noised woods SAR image by all de-noised method (a) De-noising by NSST (b) De-noising by NL-LMSE (c) De-noising by GNL (d) De-noising by GNL-NSST (e) De-noising by BSSR (f) De-noising by ours

Fig.2 and Fig.3 show that the NSST makes the edge blurry. After de-noising, the GNL-NSST and GNL removed some textures of the edge. NL-LMSE, BSSR produces some man-made texture. The proposed method not only suppresses the man-made texture but also retains the edge and texture. What’s more, the two test images are special: one has rich texture (Fig.1 (a)), and the other has poor texture (Fig.1 (b)). So the test images are very typically to test all the de-noised methods.

We have calculated several common de-noising performance parameters to evaluate the algorithms above, which contain PSNR, equivalent numbers of looks (ENL), standard deviation (Sd) and edge preservation index (EPI), as shown in Table 1 and 2. In addition, the larger PSNR here shows the de-noising algorithm ability is strong, the greater ENL shows better visual effects of the de-noising algorithm, while the EPI greater and the Sd smaller the de-noising algorithm can maintain more details.

Table 1. The performance of Fig 2.

The de-noised methods	PSNR (db)	ENL	Sd	EPI
NSST	31.55	15.56	28.73	0.88
NL-LMSE	32.43	20.11	29.07	0.92
GNL	31.78	19.89	28.35	0.90
GNL-NSST	35.01	20.65	29.78	0.95
BSSR	34.33	19.90	29.57	0.94
Ours	35.13	21.05	27.88	0.96

Table 2. The performance of Fig 3.

The de-noised methods	PSNR (db)	ENL	Sd	EPI
NSST	33.11	22.45	33.45	0.90
NL-LMSE	35.77	23.68	34.01	0.97
GNL	34.56	22.84	33.59	0.93
GNL-NSST	36.67	25.55	35.67	0.98
BSSR	35.85	24.19	35.15	0.97
Ours	36.78	26.57	33.22	0.98

From table 1 and 2, we can know that the proposed method performs better.

4. Conclusion

In this paper, a new SAR image de-noising method based on GNL-means with optimized pixel-wise weighting in NSST domain is proposed. The experimental results show that the new method can both preserve the edge and texture effectively and suppress the man-made texture to get better visual effect. However, there exist some disadvantages in our method, such as the processing time of de-noising process is longer than GNL and GNL-NSST. In next research, we will try to find a method to improve it.

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