A CNN-BASED METHOD FOR SAR IMAGE DESPECKLING

Dejiao Ma[1], Xiaoling Zhang[2], Xinxin Tang[3], Jing Ming[4], Jun Shi[5]

University of Electronic Science and Technology of China, Chengdu，Sichuan 611731，China

ABSTRACT

In this paper, to remove the speckle noise of SAR images, we propose a modified method for SAR image despeckling based on Convolutional Neural Networks (CNNs). The network uses dilated convolutions for feature extraction, which can extend the receptive field and prevent too many layers that may result in computational burden and low efficiency. The network also uses residual learning to accelerate training procedure and improve performance for SAR image despeckling. Experimental results show that the proposed method achieve good performance for SAR image despeckling both on simulated and real data. And compared with the traditional despeckling methods, the proposed method has better performance and higher efficiency.

Index Terms**—**SAR image despeckling; convolutional neural networks; dilated convolution; residual learning

1. INTRODUCTION

Synthetic Aperture Radar (SAR) is an active high-resolution imaging sensor that can perform all-day, all-weather observations. SAR has a wide range of applications in military and civilian applications. However, due to the coherence of the scattering phenomenon [1], SAR images are inevitably accompanied by speckle noise. The speckle noise seriously affects the quality of SAR images, bringing great challenges to subsequent image segmentation, region of interest extraction, target detection, target recognition, etc. [2], and greatly reduces the utilization of SAR images. Therefore, SAR image despeckling is the basic work of post-processing of SAR images and has important research value.

To improve the quality of SAR images, researchers have proposed a large number of methods, mainly including multi-view processing before imaging and speckle filters after imaging. Multi-view processing causes damages to resolution and detail of SAR images while reducing speckle noise. The main despeckling techniques can be loosely grouped in three categories: spatial domain filters, transform domain filters and variational approaches. Spatial domain filters such as Lee filter [3], Mean filter [4], Frost filter [5] cannot preserve image edges and details due to the nature of local processing. To solve this problem, the nonlocal means algorithm (NLM) [6] was proposed, but the application is limited because of computational burden and low efficiency caused by the similar search steps. The representative of transform domain filters [7-8] are the wavelet-based threshold filters. SAR-BM3D algorithm [9] is one of the best transform domain methods, which combines the non-local idea with transform domain filters, but its low efficiency because of a large number of search limits its application. Variational approaches [10] have achieved good performance of SAR image despeckling, but the result is usually dependent on the choice of the model parameter.

In the past few years, the rapid development of deep learning provides a new research direction for SAR image despeckling. Convolutional Neural Networks (CNNs) are the most widely used models in the field of target recognition and target detection. Paper [11] proposed a method based on CNNs for Additive white Gaussian noise (AWGN) image denoising, which gain good performance. Paper [12] proposed a novel deep neural network based method named SAR-DRN, learning a no-linear end-to-end mapping between the speckled and clean SAR images. Here, following the SAR-DRN in paper [12], we propose a modified method based on CNNs. We build a network based on dilated convolutions and residual learning with less layers and simpler connections, which can reduce memory usage and time cost. Dilated convolutions are used for feature extraction, which can extend the receptive field prevent too many layers that may result in computational burden and low efficiency. Experimental results show that the proposed method achieve good performance for SAR image despeckling both on simulated and real data.

The paper is organized as follows: Section 2 introduces the model of the proposed method, including residual learning strategy, dilated convolutions and training procedure. Section 3 presents experimental results on simulated and real SAR data, as well as analysis and comparisons between the traditional methods and the proposed method. The conclusions are summarized in Section 4.

2. A CNN-BASED METHOD FOR SAR IMAGE DESPECKLING

Inspired by SAR-DRN [12], we propose a CNN-based method for SAR image despeckling. We build a lighter network with dilated convolutions and residual learning, the architecture of which is shown in Fig.1. The network comprises 5 layers, with no pooling. From the first layer to the forth layer, each layer contains dilated convolution and activation function. The last layer contains only a dilated convolution. Residual learning, dilated convolutions and training procedure are introduced in the following.

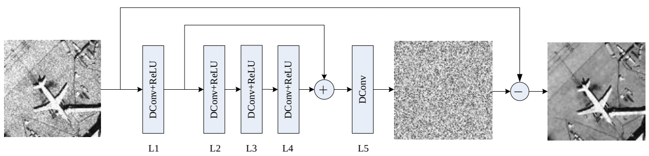

Fig. 1. The architecture of the proposed method

2.1. Residual Learning

Residual learning strategy [13] which add some short connections in hidden layers of the network can accelerate training procedure and improve performance. Residual learning strategy is applied in our network as shown in Fig.1, leading to two short connections. One short connection add a line from the first layer output to the forth layer output, another short connection add a line from the network input to the fifth layer output. With residual learning strategy, the loss function used in our model can be expressed as:

$$loss(\Theta) = \frac{1}{2N} \| \phi(y_i, \Theta) - (y_i - x_i) \|_2^2 \qquad (1)$$

where Θ donates the trainable parameters, y_i is the speckled image, x_i is the clean image, $\phi(y_i, \Theta)$ represents the noise distribution the network learned through training, $\{(y_i, x_i)\}_{i=1}^{N}$ is a collection of N training image pairs.

2.2. Dilated Convolutions

Dilated convolutions [14] can extend the receptive field with less layers and reduce computational burden and low efficiency caused by too many layers. We use dilated convolutions in our model. The common convolution receptive field has a linear correction with layer depth i:

$$F_{depth-i} = (2i+1) \times (2i+1) \qquad (2)$$

While the dilated convolution receptive field has an exponential correction with layer depth i:

$$F_{depth-i} = (2^{i+1}\text{-}1) \times (2^{i+1}\text{-}1) \qquad (3)$$

Setting kernel size= 3×3 as an example, Fig.2 shows the dilated convolution receptive field size.

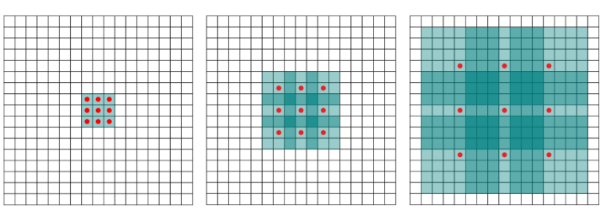

Fig. 2. Dilated convolution receptive field size.

As is shown in Fig.2, (a) Illustrates that a 1-dilated convolution has a receptive field of 3×3, the same size as common convolution. (b) Illustrates that a 2-dilated convolution has a receptive field of 7×7. (c) Illustrates that a 2-dilated convolution has a receptive field of 15×15.

We use dilated convolutions in our model. In Fig.1, the kernel size is set to 3×3 and the dilation parameters of the dilated convolutions from layer 1 to layer 5 are respectively set to 1, 2,3,2,1. Equation (3) and Fig.2. show that dilated convolutions can obtain a larger receptive field and more features than common convolutions with no more extra parameters.

Compared with SAR-DRN in paper [12], our network structure is much simpler. With less layers and parameters, our network still maintain the receptive filed size, reduce memory usage and time cost.

2.3. Training Procedure

Fig.3. presents the training procedure of our network. Since real SAR images inevitably have coherent speckle noise, we use optical images as original clean images. Based on the speckle noise distributions of the SAR images, the speckle noise is added to the original clean image to obtain SAR speckled images, which are used as input to train the network. By optimizing the weight and minimizing the loss function, we get a trained network, which can learn the noise characteristics of the SAR images.

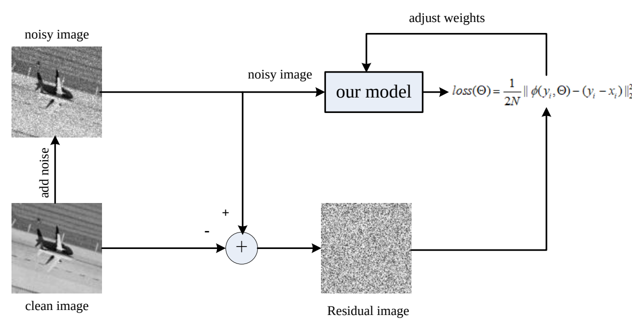

Fig. 3. Training procedure

3. EXPERIMENTAL RESULTS

We use simulated and real SAR data to verify the effectiveness of the proposed method.

3.1. Training and Test Datasets

To train and test our model, we choose 400 images of size 256×256 and set patch size as 30×30 and stride=10 from the UC Merced land-use dataset [15]. Forty percent of the datasets is randomly selected as the training set, while the rest is used as the test set. To improve performance and enhance the generalization ability of the network, we also perform some data argumentations. The original clean images are rotated at intervals of 45 degrees, 90 degrees, 180 degrees, and 270 degrees, and so we get a large number of multi-angle images.

To test our model on real SAR image despeckling, we use San Francisco SAR image (cropped to 620×620).

For the network, the learning rate is initialized to 0.0001 using Adam algorithm [16]. The training and test procedure uses tensorflow in Windows 10 environment, with an intel(R) core(TM) i5-6400 CPU at 2.70 GHz and ROM 8GB.

3.2. Experimental Results

We generate five speckle noise level of $L=1,2,3,4,5$ to verify the effectiveness of the proposed model. NL-SAR [17] and SAR-BM3D [18] are good traditional methods for SAR image despeckling. SAR-DRN [12] is a CNN-based method. We analysis and compare despeckling performance as well as calculation time with three despeckling methods, NL-SAR, SAR-BM3D and SAR-DRN.

Firstly, we use visual assessment to evaluate despeckling performance of the proposed method and the mentioned three methods. Fig.4. shows results of different despeckling methods on simulated SAR images with speckle noise level L=5.

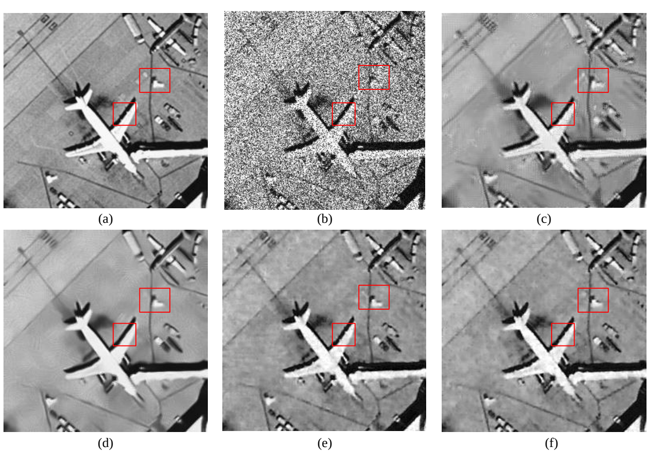

Fig.4. Results on simulated SAR image with speckle noise level L=5. (a) Original image; (b) Speckled image; (c) SAR-BM3D; (d) NL-SAR; (e) SAR-DRN; (f) Ours

It can be seen from Fig.4. that the all four methods can remove SAR speckle noise and improve image quality. From the red boxes in Fig.4., we can see that the image denoised by SAR-DRN and our method have higher similarity to the original clean image. The texture of the airplane wing edge and the contour of the local position are clearer, and the edge and detail information of the image are better preserved while removing the speckle noise.

To better quantitatively compare the denoising effect between our method and the above three methods, we use Peak Signal to Noise Ratio (PSNR) [19] as an objective evaluation indicator. The larger the PSNR, the better the image quality, and the higher the similarity with the reference image, indicating that the despeckling effect is better. Tab.1 reports PSNR results for SAR image despeckling using four different methods.

Tab. 1 PSNR over simulated SAR images

Noise level	L=1	L=2	L=3	L=4	L=5
SAR-BM3D	29.86	27.24	26.52	24.39	22.27
NL-SAR	27.81	26.59	25.65	24.67	23.12
SAR-DRN	32.52	31.32	30.56	28.45	27.44
ours	32.73	31.36	30.99	28.61	27.62

As shown in Tab.1, the proposed method performs the best in PSNR value with all five noise level compared with the other three methods, indicating that the proposed method achieve better performance on removing noise of different intensities and has a stable despeckling effect on high-intensity noise.

Calculation time complexity is also an important indicator for evaluating the performance of a method. Tab.2 shows calculation time for despeckling an image of size 256×256 using four despeckling methods.

Tab. 2 CPU time for despeckling a 256×256 clip

METHOD	SAR-BM3D	NL-SAR	SAR-DRN	ours
time(s)	19.17	2.23	1.46	0.95

Tab.2 shows that the proposed method cost less time than the other three methods, only 0.95 seconds for a 256×256 clip. The proposed method has higher efficiency and shows superior performance over calculation time.

We also compare our method with the three state-of-the-art methods mentioned above on the real SAR image. The real SAR image despeckling results are shown in Fig.6. The ENL values are estimated from the chosen region (the red box in Fig.4(a)) and are shown in Tab.3. The calculation time is presented in Tab.4.

Tab. 3 ENL for the chosen region

METHOD	SAR-BM3D	NL-SAR	SAR-DRN	ours
ENL	18.86	15.72	21.35	21.93

Tab. 4 CPU time for despeckling a 620×620 clip

METHOD	SAR-BM3D	NL-SAR	SAR-DRN	ours
time(s)	125.72	14.16	5.88	3.64

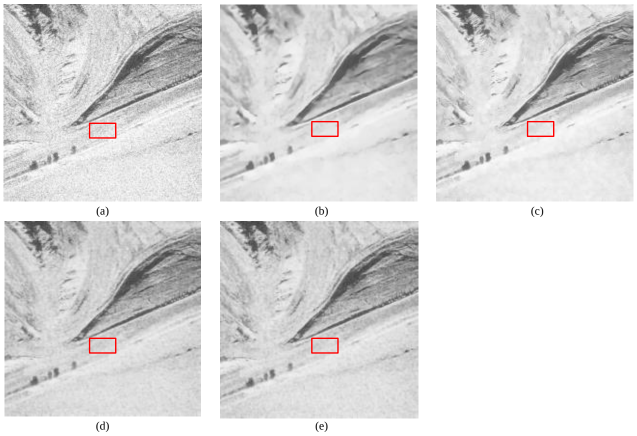

Fig.5. Results on real SAR image. (a) Original image; (b) SAR-BM3D; (c) NL-SAR; (d) SAR-DRN; (e) Ours

Fig.5, Tab.3 and Tab.4 shows that the proposed method achieves good performance on SAR speckle noise removal. And compared with NL-SAR, SAR-BM3D and SAR-DRN, the proposed method has advantages in despeckling performance and calculation time.

4. CONCLUSION

To improve qualities, preserve detail and texture information in SAR image despeckling, we propose a modified CNN-based method inspired by SAR-DRN [12]. We build a lightweight network structure using dilated convolutions and residual learning strategy, which can reduce computational burden, accelerate training procedure and improve despeckling performance. Experimental results show that the proposed method obtain better results in despeckling performance and efficiency compared to the state-of-the-art methods.

5. REFERENCES

[1] J. W. Goodman, “Some fundamental properties of speckle,” J. Opt. Soc. Am., vol. 66, no. 11, pp. 1145 – 1150, 1976.

[2] H. Liu, S. Yang, S. Gou, P. Chen, Y. Wang, and L. Jiao, “Fast Classification for Large Polarimetric SAR Data Based on Refined Spatial-Anchor Graph,” IEEE Geosci. Remote Sens.

[3] Zomet, Assaf, Alex Rav-Acha, and Shmuel Peleg. "Robust super-resolution." Computer Vision and Pattern Recognition, 2001. CVPR 2001. Proceedings of the 2001 IEEE Computer Society Conference on. Vol. 1. IEEE, 2001.

[4] Lee, Jong-Sen. "Speckle suppression and analysis for synthetic aperture radar images." Optical engineering 25.5 (1986): 255636.

[5] Frost, Victor S., et al. "A model for radar images and its application to adaptive digital filtering of multiplicative noise." IEEE Transactions on Pattern Analysis & Machine Intelligence 2 (1982): 157-166.

[6] C. A. Deledalle, L. Denis, and F. Tupin, “Iterative weighted maximum likelihood denoising with probabilistic patch-based weights,” IEEE Trans. Image Process., vol. 18, no. 12, p. 2661,2009.

[7] Datcu, Mihai. "Wavelet-based despeckling of SAR images using Gauss–Markov random fields." IEEE Transactions on Geoscience and Remote Sensing 45.12 (2007): 4127-4143.

[8] Ni, Wei, B. L. Guo, and Yang Liu. "Speckle reduction algorithm for SAR images using contourlet transform." J. Inf. Comput. Sci.(JOICS) 3.1 (2006): 83-94.

[9] S. Parrilli, M. Poderico, C. V. Angelino, and L. Verdoliva, “Anonlocal SAR image denoising algorithm based on LLMMSE wavelet shrinkage,” IEEE Trans. Geosci. Remote Sens., vol. 50, no. 2, pp. 606 – 616, 2012.

[10] Feng. W, Lei. H, Gao. Y, “Speckle reduction via higher order total variation approach,” IEEE Trans. Image Process., vol. 23, no. 4, pp. 1831 – 1843, 2014.

[11] K. Zhang, W. Zuo, Y. Chen, D. Meng, and L. Zhang, “Beyond a Gaussian Denoiser: Residual Learning of Deep CNN for Image Denoising,” arXiv:1608.03981v1, 2016.

[12] Zhang Q, Yuan Q, Li J, et al. Learning a dilated residual network for SAR image despeckling[J]. Remote Sensing, 2018, 10(2): 196.

[13] K. He, X. Zhang, S. Ren, and J. Sun, “Deep Residual Learning for Image Recognition,” in IEEE CVPR, 2016, pp. 770 – 778.

[14] F. Yu and V. Koltun, “Multi-scale context aggregation by dilated convolutions,” arXiv preprint arXiv:1511.07122, 2015.

[15] Y. Yang and S. Newsam, “Bag-of-visual-words and spatial extensions for land-use classification,” in Proc. 18th SIGSPATIAL Int. Conf. Advances in Geographic Information Systems, 2010, pp. 270 – 279.

[16] Kingma, Diederik P., and Jimmy Ba. "Adam: A method for stochastic optimization." arXiv preprint arXiv:1412.6980 (2014).

[17] D.P. Kingma and J. Ba, “Adam: A method for stochastic optimization,” in International Conf. on Learning Representations (ICLR), 2015.

[18] S. Ioffe and C. Szegedy, “Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift,” arXiv:1502.03167v3, 2015.

[19] Huynh-Thu, Quan, and Mohammed Ghanbari. "Scope of validity of PSNR in image/video quality assessment." Electronics letters 44.13 (2008): 800-801.