

A Self-Supervised Method Based on Noise2Noise Model for SAR Image Despeckling

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Abstract

Synthetic aperture radar (SAR) imaging plays an important role in recent earth observation research, which is a form of radar imaging technology that collects information with a high spatial resolution even in adverse weather and lighting conditions. Different from optical images, SAR images are contaminated by speckle noises and the presence of speckle noises in SAR images makes it difficult to understand and be widely applied. A self-supervised speckle denoising model is proposed in this paper based on the Noise2Noise model. The experimental results show that the proposed method can preserve details and reduce smoothing not only in speckle noise multiplicative domain but also additive domain. The tentative study demonstrates the potential of SAR images despeckling without clean data.

I. Introduction

Synthetic aperture radar (SAR) is a coherent radar imaging method, which produces high resolution images of targets and landscapes. The radar emits electromagnetic radiation and measures the reflected waves of the target to obtain SAR images.

Among the traditional image noise reduction methods, the simpler methods often have limited effects, and the methods with better effects are difficult to achieve real-time operation due to their huge amount of calculation. With the emergence and development of the deep learning algorithms, the image denoising methods based on the deep neural networks have gradually been widely used. The existing fully supervised image denoising networks need to be trained on a data set composed of a large number of noisy-clean paired images. In some cases, it is difficult to obtain the ground truth images without noises, however can acquire several noisy images of the same scene. The Noise2Noise model offers a framework to train a network by only using noisy images [1].

For the SAR images, we do not have a completely noise-free image. Therefore, it is very difficult to construct the noisy-clean image pair SAR images. We proposed a speckle removal architecture by studying the structure of the Noise2Noise model and the U-Net model [2].

II. Main Results

2.1 Speckle Noise Model

The speckle is a granular interference that inherently exists in and degrades the quality of the active radar, the SAR, medical ultrasound, and optical coherence tomography images. The speckle

phenomenon has an appearance like noise and poses problems to the SAR image interpretation. According to the SAR imaging principle, the Goodman model from [3] describes that the measured intensity image I can be related to the reflectivity R through multiplicative model $I = R \times S$, where the speckle component S is a random variable that follows a gamma distribution:

$$p(S) = \frac{L^L}{\Gamma(L)} S^{L-1} \exp(-LS), \quad (1)$$

where $L \geq 1$ is the number of looks and Γ is the gamma function. The speckle noise is signal dependent.

When training a neural network for speckle denoising, it is often beneficial to apply a logarithmic transform input SAR intensity [4]. Considering the log of the intensity Y instead of I transforms the speckle noise into an additive component: $Y = X + N$ as depicted in Fig. 1, where N follows a Fisher-Tippett distribution as

$$p(N) = \frac{L^L}{\Gamma(L)} e^{LN} \exp(-Le^N). \quad (2)$$

With $Y = \ln I$ representing the log-intensity, $X = \ln R$ represents the log-reflectivity, $E(Y) = X - \ln L + \psi(L)$, $Var(Y) = \psi(1, L)$. ψ is the digamma function, $\psi(1, L)$ is the polygamma function of L . As it can be seen above, the speckle has a non-zero mean after logarithmic transform that fluctuations are signal independent now.

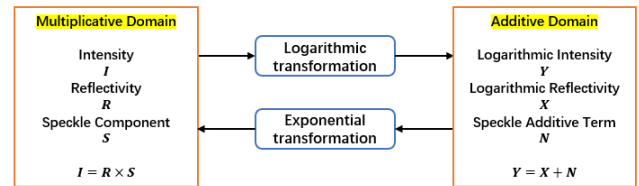


Figure.1 SAR image homomorphic transform.

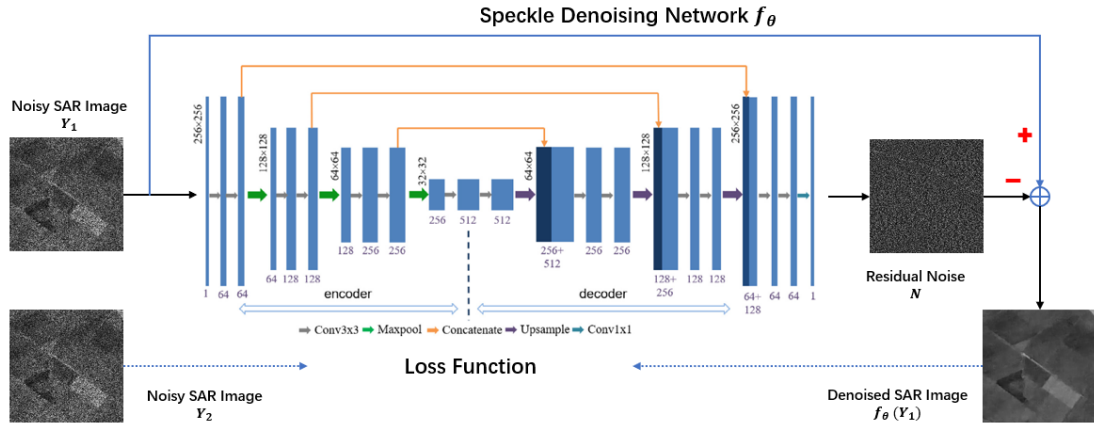


Figure.2 The structure of the SAR speckle denoising network.

2.1 The Proposed Method

We propose to transform the multiplicative noise into an additive noise for the proposed method to remove the speckle noise easier by the residual way. Figure 2 shows the architecture of the proposed network. We developed a modified version of U-Net [2], which is an encoder-decoder convolutional neural network originally proposed for image segmentation tasks. In the original supervised learning methods, pair of noisy and clean images are available for training. The Noise2Noise method replace the ground truth image by another noisy image. The training is asymptotically equivalent to a supervised training with the unknown logarithmic reflectivity. Given several pairs of noisy images (Y_1, Y_2) drawn under the same conditional distribution, the proposed method tries to minimize the following loss in terms of θ when training a neural network.

$$\operatorname{argmin}_{\theta} E_{Y_1} \{E_{Y_2|Y_1} [l(f_{\theta}(Y_1), Y_2)]\}, \quad (3)$$

where f_{θ} is the speckle denoising network parameterized by θ . In this paper, we only discuss the situation of the single look ($L = 1$). Therefore, $E(Y) = X - \psi(1)$. We optimize (3) with $L2$ loss function as

$$l(f_{\theta}(Y_1), Y_2) = \|f_{\theta}(Y_1) - Y_2 + \psi(1)\|_2^2. \quad (4)$$

III. Experiment Results

The dataset consists of large-scale real speckle noisy images from Sentinel-1 [5]. Paired noisy images were generated with synthetic speckle noises based on the speckle noise model, one used as input, another used to calculate the loss during training. The images are divided into patches of 256×256 . The training set is composed by 2,800 image patches. We evaluate experimental results with the peak-signal-to-noise-ratio (PSNR). We test the despeckling in the multiplicative domain with the speckle as a multiplicative noise, and the additive domain with the speckle as an additive noise. Figure 3 show quantitative sample results of the experiments with PSNR values after 300 iterations. By comparing the PSNR values, the experimental results in the domain of multiplicative are better. However, the results of the additive domain provide sharper results and retain more details.

In this paper, the proposed method shows that in the absence of the real clean ground truth SAR images, we can also perform the SAR image speckle denoising based on the Noise2Noise and U-Net models.

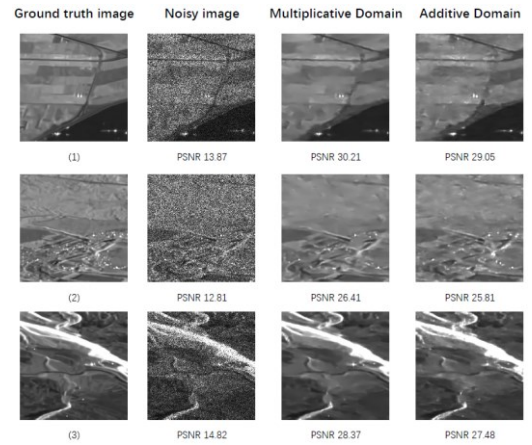


Figure3. Sample results of different domains.

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