Deeper FFDNet Based SAR Image Despeckling
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Abstract

Remote sensing (RS) plays an important role in recent earth observation research and synthetic aperture radar (SAR) is widely applied for active remote sensing. The 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 speckle denoising model is proposed in this paper that uses residual networks and FFDNet network. The experimental results show that the proposed method can preserve details and reduce smoothing better than the scheme only based on the original FFDNet.

1. Introduction

Synthetic aperture radar (SAR) is an all-day and all-weather active remote sensing imaging radar, which is used to construct 2D images or 3D reconstructions of objects such as landscapes. The SAR system acquires images by transmitting electromagnetic waves and processing the received echoes to reconstruct the image. These reflected echoes are mainly interfered by the signals generated by the uneven surface and the mutual coupling array, which causes the system to add fuzzy and irrelevant information to the reconstructed image called the speckle noise [1]. Different from the Gaussian noise of optical images, the speckle noise is spatially correlated and signal related, which greatly affects the interpretability of the image and scientific exploitation.

Many researchers have proposed several filtering techniques to remove the speckle noise, most of which are based on statistical methods such as Lee Filter, Kuan Filter, BM3D, to name a few [2]. However, due to their local processing characteristics, these methods can cause blur or artifacts, and therefore cannot retain necessary features for the subsequent processing. Recently, there are also some works on interpreting SAR images through deep learning. SAR-CNN (Convolutional Neural Network) first converts the SAR image into a logarithmic space and maps it to the denoised image through 17 layers CNN [3]. There is also speckle denoising based on modified FFDNet to handle a range of noise level [4]. These works have shown great performance in removing SAR image speckle noise, and it can be observed that these works inherit the characteristics of the ResNet architecture [5].

Inspired by these works, we propose in this paper a speckle removal architecture by studying the structure of FFDNet [6] and ResNet with their applicability in SAR image despeckling. The main contributions of this paper are as follows. First, we propose a flexible architecture based on deep learning to remove speckle noise from SAR images. The proposed scheme adds an additional noise level map as simultaneous input and combines the residual blocks and the FFDNet.

2. Speckle Noise

Speckle is a granular interference that inherently exists in and degrades the quality of the SAR images. The speckle phenomenon has an appearance like noise and poses problems to the SAR image interpretation. According to SAR imaging principle, Goodman model [7] describes the measured intensity $I$, the reflectivity $R$ and the amplitude $A = \sqrt{I}$ for simulating the speckle phenomenon. The intensity follows a gamma distribution with the following probability density function.

$$p_{I}(I|R) = \frac{L^L I^{L-1}}{\Gamma(L) R^L} \exp\left(-\frac{L I}{R}\right),$$  \hspace{1cm} (1)

where $I$ is the image intensity, $R$ is the image reflectivity, $\Gamma$ is the gamma function, and $L$ is the number of looks.

The intensity $I$ can be decomposed into a product of the reflectivity $R$ and a speckle component $S$ as

$$I = R \times S, \quad E(I) = R, \quad \text{Var}(I) = \frac{R^2}{L}. \hspace{1cm} (2)$$

1.1 The Proposed Architecture

The FFDNet [6] was proposed for removing spatial variant additive white Gaussian noise (AWGN) in optical images. We focus in this paper on combining the ResNet and FFDNet instead of designing a new architecture. The proposed method retains the ability of FFDNet to handle various noise level. The architecture of the proposed network is shown in Figure 1(a). Here, the “Residual Blocks” is composed of four residual blocks. Each residual block consists of two convolutional layers and one ReLU activation layer as shown in Figure 1(b). There are 3 identity skip connections between 2×2 stride convolution downsampling and 2×2 transpose convolution up-sampling operations. The whole network has four scales as the number of channels are 64, 128, 256, 512 from the first scale to the fourth.

The noise level map is used to manage the balance of noise reduction and detail preservation, which specifies a particular noise level for each pixel of the image. The noise level map can be determined by local means method or other.
The proposed method learns a mapping $F$ from the noise image $Y$ and the noise level map $M$ to the denoised image $\hat{X}$ with the learning weight $\theta$ as

$\hat{X} = F(Y, M; \theta).$  

The proposed method uses $L_1$ as the loss function for easier convergence.

$Loss(\theta) = \|F(Y, M; \theta) - X\|_{L_1}.$  

3. Experiment Results

The data set consists of 7 pairs of large-scale real speckle noisy and denoised images from Sentinel-1 [8]. We randomly clip and choose 1,232 patches as a training set and use the Adam optimizer. During training, the noise map is a uniform map, and the noise level is randomly chosen from [0, 50]. For each iteration, 16 patches with size 128×128 were randomly selected from the training dataset. We compare the proposed method with other denoising method based on the FFDNet only. The peak signal-to-noise ratio (PSNR) and the structural similarity index measure (SSIM) are used for evaluating the speckle denoising results. Figure 2 provides sample results after 5,000 iterations with the noise level map of 50. Our proposed network consists of residual blocks and skip connections that play an important role in learning to do speckle denoising without losing details.

4. Conclusion

In this paper, the proposed method was combined by the FFDNet and the ResNet for SAR image speckle denoising. The experiment results show that the proposed method can preserve details and reduce smoothing better than the scheme only based on the original FFDNet. There is a lack of real clean SAR images for data-driven supervised learning. Therefore, it is a general trend to apply an unsupervised learning for the speckle denoising task [3]. In the future, we will conduct follow-up research for SAR image despeckling.

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References


