Use of Deep Learning for Speckle Reduction in SAR Images

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Summary

The problem of speckle removal from single look synthetic aperture radar (SAR) images has been addressed through the adaptation of the U-Net convolutional neural network. This architecture allows for the extraction of features at different scales and it is capable of producing detailed reconstructions through its system of skip connections. This makes it suitable for the specific task, which requires removing the speckle from SAR images while preserving their structural information. The proposed approach takes advantage of this network, which has been modified and optimized accordingly. During the learning phase, a modified version of the total variation (TV) regularization has been adopted to improve the network performance when dealing with real SAR data. Finally, experiments have been carried out on simulated and real data to compare the performance of the proposed method with respect to what available in literature.

Methodology

1. U-Net Convolutional Neural Network

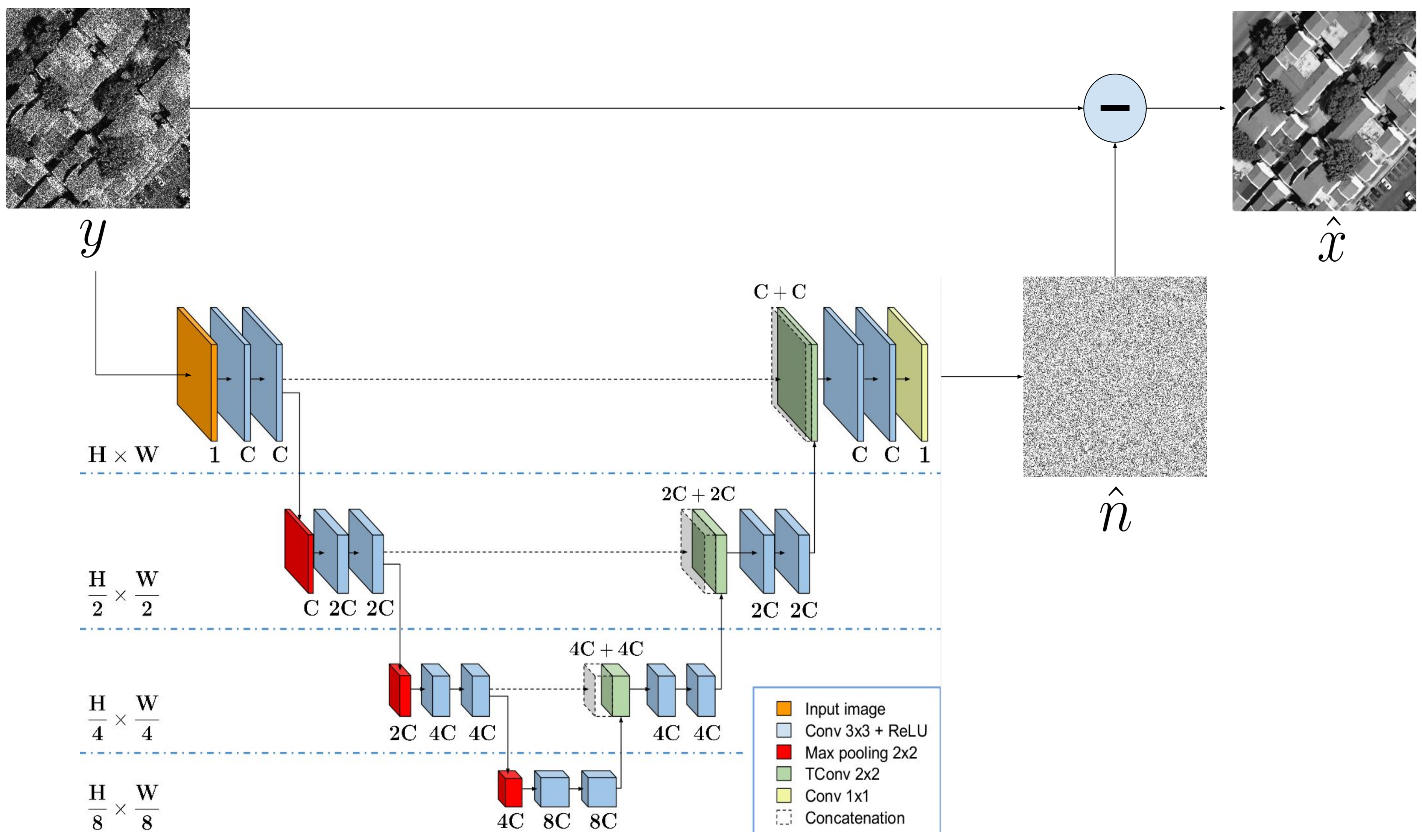
In this work we adapted U-Net, an encoder-decoder 4-levels depth architecture.

Encoder-Decoder:

- Each level of the encoder network, except the first one, is composed by a max-pooling layer followed by two stacked convolutional layers, each one employing the rectified linear unit (ReLU) as non-linear activation.
- The decoder network mirrors the encoder. It is composed, at each level, by a 2 x 2 Transposed Convolution, as upsampling layer, and two stacked convolutional layers.

Skip-Connections:

- The feature maps after the upsampling are concatenated with the corresponding encoding output. This allows the low-level information to be transmitted to high-resolution layers and, at the same time, it helps the learning by solving the known vanishing gradient problem.

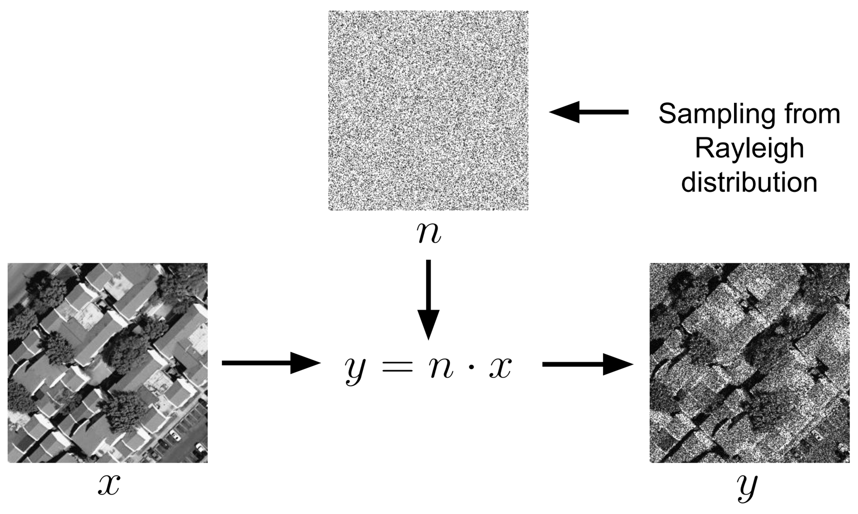


2. Residual Learning

Given the input speckled image y, the network is trained to extract the residual noise $\hat{n}$ instead of predicting directly the speckle-free image [1]. At inference time, the despeckled image $\hat{x}$ is obtained from the speckle image by subtracting the predicted residual noise.

3. Speckle Model

In order to simulate speckled images we employed the multiplicative model $y = nx$, where y is the observed image, x is the speckle-free amplitude value, and n is the speckle noise random variable which, in case of single look SAR image, obeys to the Rayleigh distribution.



4. Datasets

- *Pre-training*: 238121 patches of 64 x 64 pixels collected from UC-Merced land use RGB dataset and converted into grayscale.
- *Fine-tuning on real SAR resolution*: 167713 patches of 64 x 64 pixels selected from two Sentinel-1 clean images obtained by averaging large data stacks.

5. Fine-tuning regularization

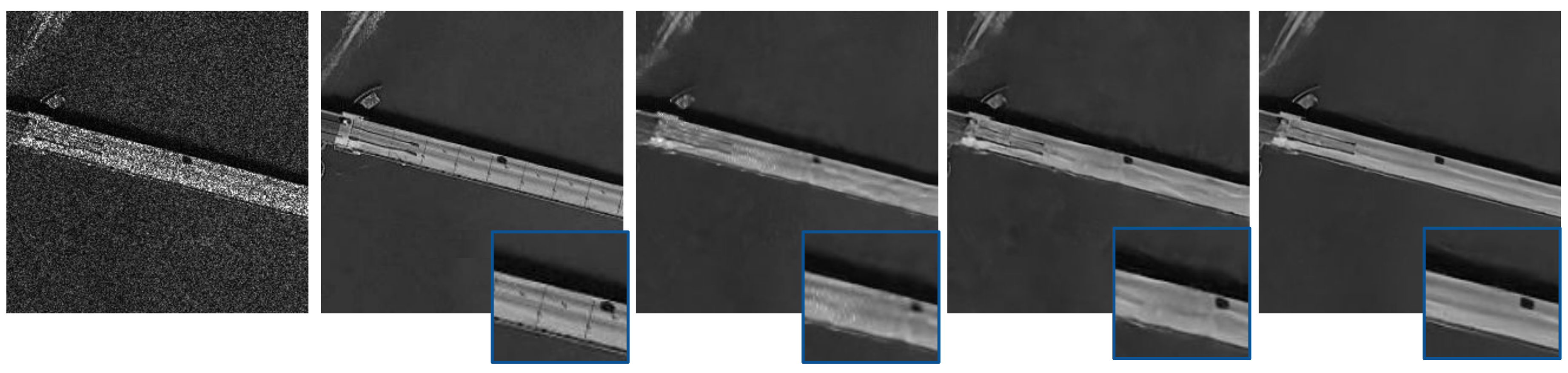
We employed the following modified version of the total variation (TV) regularizer

$$L_{TV} = e^{-|\nabla_h x|}|\nabla_h \hat{x}| + e^{-|\nabla_v x|}|\nabla_v \hat{x}|$$

Results

The obtained results show the ability of the proposed approach to remove the speckle noise from both synthetic and real SAR images. The reconstructed speckle-free images are less affected by artificial artifacts or residual speckle w.r.t. other baseline approaches [1][2]. The qualitative results demonstrate how the employed network allows removing speckle noise, also testified by the high peak signal-to-noise ratio (PSNR) computed on test set, while preserving the structural details of the images, as confirmed by the Structural Similarity Index (SSIM). For what concern the real domain, we report the Equivalent Number of Looks (ENL), which is indicative of the amount of speckle removed in homogeneous regions (red boxes). Below we show how the learned model generalizes well also on SAR resolutions (COSMO-SkyMed and RADARSAT) not included in the training set, whose images are collected only from the Sentinel-1 mission. Finally, we show a comparison between U-Net and DespecKS [3], an algorithm that uses the temporal information of a whole SAR data stack. The proposed network shows better performance in preserving the details of the image.

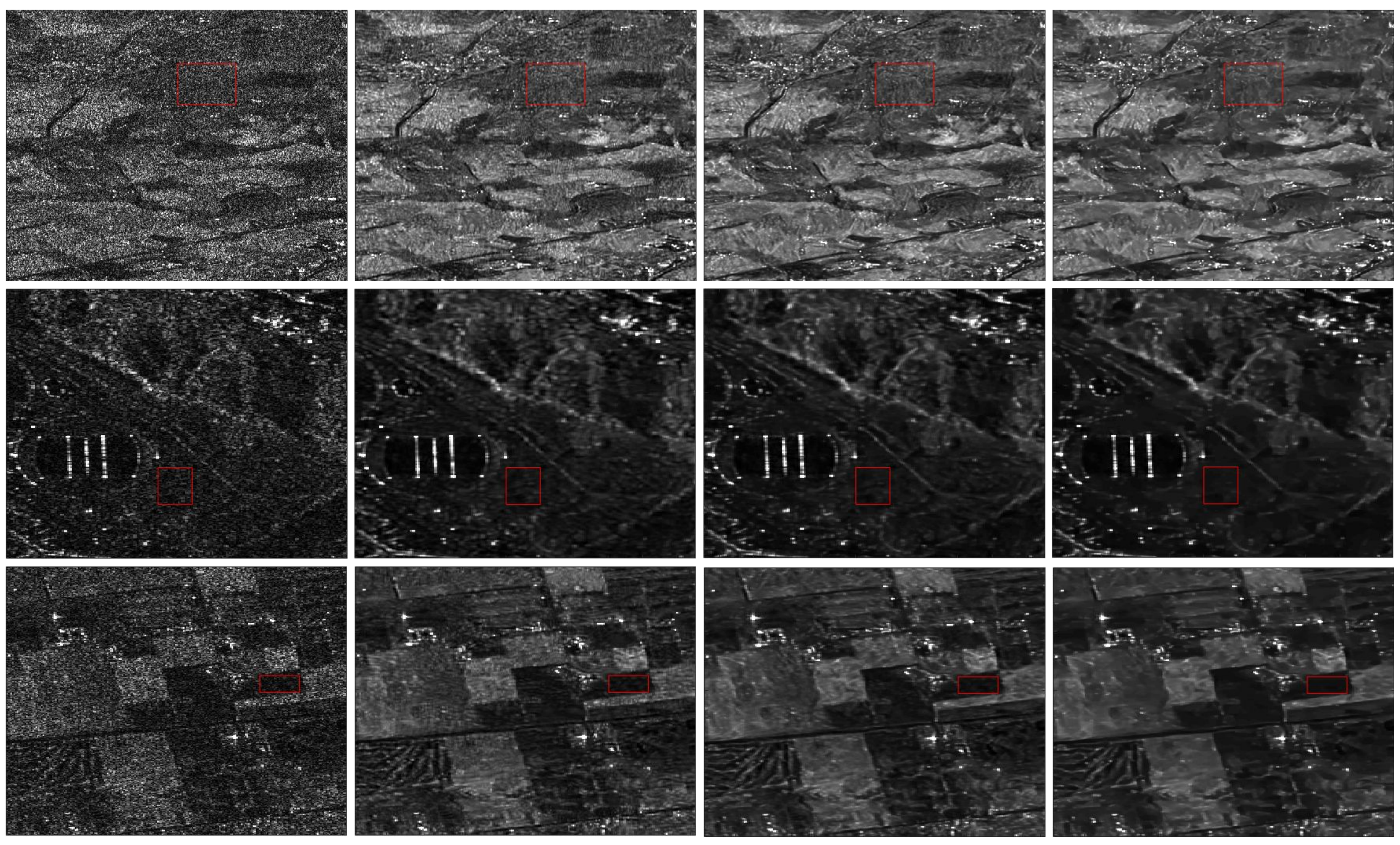
1. Synthetic Airborne Images



Original SAR-BM3D SAR-DRN Ours

	Bridge				Basketball court				Christmas tree farm				Transformer station			
	PSNR		SSIM		PSNR		SSIM		PSNR		SSIM		PSNR		SSIM	
	mean	std	mean	std	mean	std	mean	std	mean	std	mean	std	mean	std	mean	std
Noisy	18.3489	0.0354	0.1748	0.0010	14.6548	0.0211	0.1093	0.0011	17.6521	0.0289	0.4735	0.0012	10.7685	0.0235	0.2496	0.0013
SAR-BM3D	29.6914	0.1222	0.8949	0.0026	28.7579	0.0516	0.6904	0.0046	28.2377	0.0733	0.8860	0.0022	20.4701	0.0627	0.6227	0.0025
SAR-DRN	30.2771	0.1271	0.9003	0.0024	29.3548	0.0995	0.7126	0.0057	29.3019	0.0524	0.9044	0.0014	22.0661	0.0588	0.7005	0.0047
Ours	**30.9079**	**0.1122**	**0.9154**	**0.0020**	**29.5644**	**0.0906**	**0.7217**	**0.0066**	**29.9250**	**0.0915**	**0.9167**	**0.0019**	**22.3491**	**0.0316**	**0.7161**	**0.0036**

2. Real SAR Images

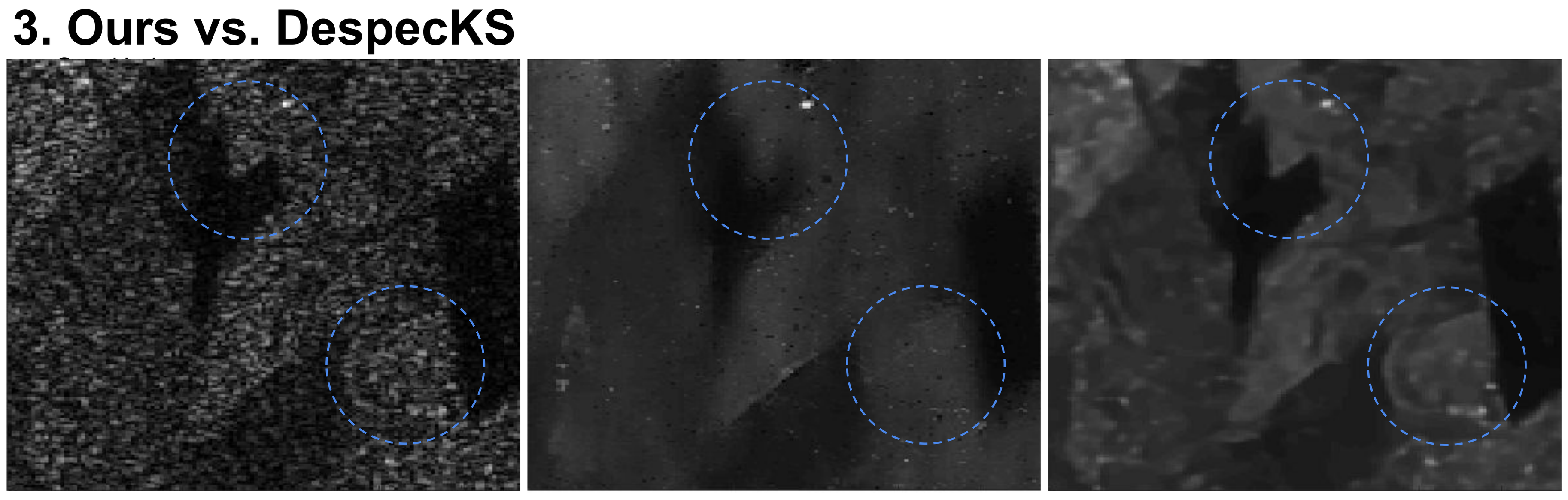


Speckled SAR-BM3D Ours (U-Net) Ours (U-Net + TV)

ENL (red regions)

	Sentinel-1	COSMO-SkyMed	RADARSAT
Noisy	3.3924	3.3495	3.7294
SAR-BM3D	22.9585	22.7635	31.7460
U-Net	31.7973	33.8462	59.9067
U-Net + TV	**43.1660**	**75.5402**	**196.8434**

3. Ours vs. DespecKS



Speckled DespecKS Ours (U-Net + TV)

References

1. Zhang, Q.; Yang, Z.; Yuan, Q.; Li, J.; Ma, X.; Shen, H.; Zhang, L. Learning a Dilated Residual Network for SAR Image Despeckling. CoRR 2017, abs/1709.02898, [1709.02898].
2. Parrilli, S.; Poderico, M.; Angelino, C.V.; Verdoliva, L. A Nonlocal SAR Image Denoising Algorithm Based on LLMMSE Wavelet Shrinkage. IEEE Transactions on Geoscience and Remote Sensing 2012, 50, 606–616. doi:10.1109/TGRS.2011.2161586.
3. Ferretti, A.; Fumagalli, A.; Novali, F.; Prati, C.; Rocca, F.; Rucci, A. A New Algorithm for Processing Interferometric Data-Stacks: SqueeSAR. IEEE T. Geoscience and Remote Sensing 2011, 49, 3460–3470. doi:10.1109/TGRS.2011.2124465.

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