Deep Learning for SAR Image Denoising

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Due to the presence of speckle noise and thermal noise in the SAR image, it is difficult to exploit the image visually and algorithmically. Traditional methods, such as Polarimetric Whitening Filter (PWF) [1], Block Matching and 3D Filtering [2], Digital Wavelet Transform [3], and Compressive Sensing [4] are available to perform denoising of SAR images, but PWF requires full Polarimetric data, and other methods are slow and/or require significant tuning effort. They may produce images with blurring effect and does not work well on dissimilar image datasets. This paper presents a new approach in SAR image denoising using a deep learning U-Net architecture [5]. The proposed method aims to produce a higher contrast SAR imagery, and works on multiple modality of images while ensuring no image artefacts.

Keywords—SAR; Denoising; Deep Learning; U-Net; Constrast Stretching

I. INTRODUCTION

Noise is inherently present in Synthetic Aperture Radar (SAR) imagery, and it exists in two main forms – speckle noise and thermal noise. Both noise types affect SAR imagery by giving the image a granular effect (salt-and-pepper), while making SAR images more challenging to exploit visually. We show two images in Figure 1 to highlight different noise contrast levels that will give rise to different exploitation experiences.

We propose to perform noise reduction for SAR imagery using a deep learning solution to enhance image contrast for better exploitation. Current technology in SAR performs denoising of SAR imagery with (i) potential tradeoffs in resolution/feature space, (ii) based on single channel imagery or (iii) requiring longer data collection by the system, which may not always be possible.

Deep learning methods for denoising SAR images are becoming popular. Methods described in [6] and [7] inject synthetic noise into satellite imagery for training the Convolutional Neural Networks (CNN). A method in [8], deSpeckNet, does generalized deep learning based SAR image de-speckling without clean imagery as reference. However, the results in the aforementioned papers appear to be overly smoothed, likely due to a poor estimation in the noise model. In [9], a multi-layered guided filtering process with CNN denoising prior is proposed, but testing is still required across more variety of images.

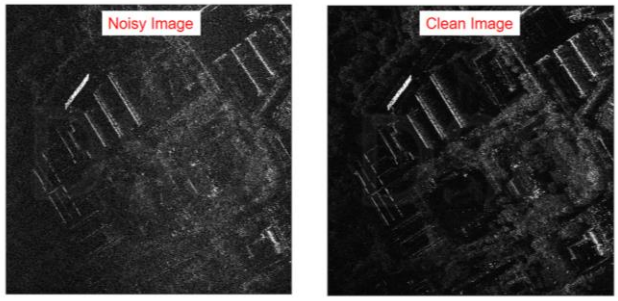

Fig. 1. Comparison between a noisy image (left) and a clean image (right). Notice that it is very difficult and exhausting to look at the details visually in the noisy image.

Our proposed denoising solution is fast and has minimal artefacts on the variety of SAR images tested. In fact, the preliminary tests show that our solution produces a high contrast SAR image, and it does not 'hallucinate' additional signatures within the scene, and is resilient to changes in image resolution.

II. DENOISING FRAMEWORK

Our solution entails the following to achieve denoising in SAR images, where Fig. 2 shows the workflow:

- Noise image data collected from SAR systems in closed-loop testing without transmission.

- Varying noise is created from this noise dataset, where we applied a random Gaussian variation of the noise on the SAR image chips of 256 x 256 from one collected SAR image. This method allows augmentation of the training data so that our training can be more successful.

- Denoising U-Net [5] is trained from scratch with the augmented database. This network is useful to improve the feature information by linking the encoder and decoder segments. Unlike Generative Adversarial Networks (GANs), the U-Net does not 'imagine' things, hence the artefacts are absent from the resultant images.

- Fine-tuning of input images is done so that our technique is resilient to resolution nor variation in SAR imaging system parameters. We adjust each image via resampling such that all the input images have a similar 'dot' size (bright point-like scatterers), and maintaining the training input resolution to pixel-size ratio for each test image.

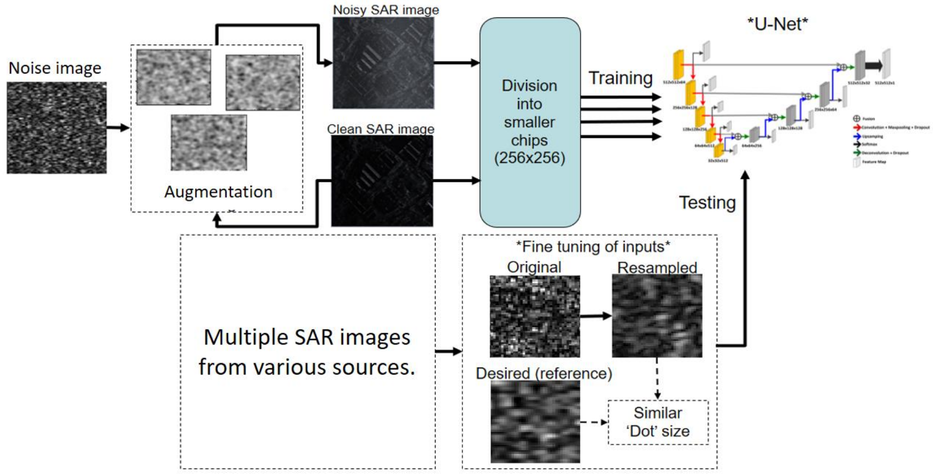

Fig. 2. Workflow diagram of our denoising solution

III. Results

Some comparisons of the results are shown in Fig. 3 and Fig. 4. A zoom-in image of a vehicle chip in Fig. 3 shows that the signatures of the vehicle are preserved using our proposed technique, which is a challenge when using classical techniques. This ensures that the downstream exploitation processing is able to work on the 'truest' target signatures for classification. In Fig. 4, we show an example of denoising on an image from a commercial sensor, ICEYE. We observe that the background noise is successfully reduced, with clearer roads and higher contrast. The network has not been trained with an ICEYE image.

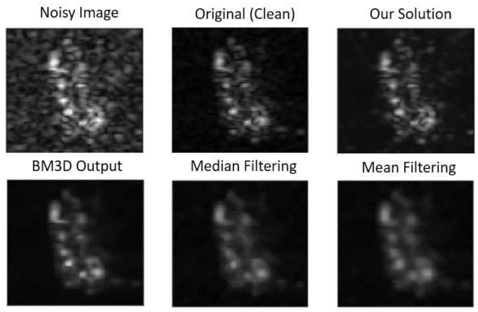

Fig. 3: Comparisons of a vehicle chip –image with injected noise (top left), original image (top middle), Image output using our technique (top right), image output after BM3D (bottom left), image output after Median Filtering (bottom middle), and image output after Mean Filtering (bottom right).

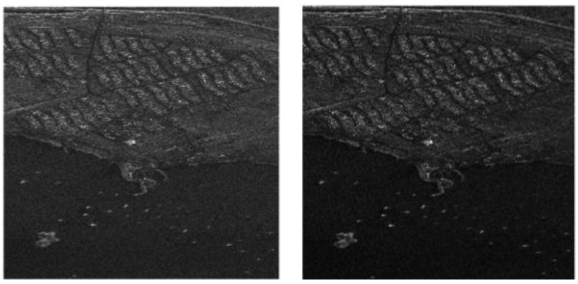

Fig. 4. Comparison of SAR images from a commercial satellite, ICEYE – before Denoising (left), and after denoising (right).

IV. Conclusions

In summary, these are the findings based on our results in Section III:

- Our results are able to achieve denoising optimally with minimal artefacts and smoothening of images.
- Data augmentation with varying noise created with Gaussian filters is effective in training our network.
- Our solution is able to work on a multitude of SAR imagery across different sensors.

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