Comparison of Despeckling techniques of SAR images

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***Abstract*—Synthetic Aperture Radar (SAR) is a method for obtaining high resolution satellite images for different kinds of terrains. This paper summarizes the results by comparison of different techniques in the area of SAR image denoising. We have implemented varied filters like Lee, Kuan and Frost filter; and used techniques like SAR-CNN, ID-CNN and ID-GAN and have made a quantitative comparison based on measures like PSNR and time taken.**

***Index Terms*—SAR, Image Processing, Despeckling, SAR-CNN, ID-CNN, ID-GAN, PSNR**

I. Introduction

A. SAR Images

Synthetic Aperture Radar (SAR) is a remote sensing technique that came from side looking airborne radar. A moving object, for example a spaceship, is used to attach SAR sensors. A huge perceived aperture is formed by the device that travels some distance in a given interval of time. The same time is taken by the pulse to return back to the antenna. Irrespective of the nature of the aperture, pixel density of the resultant image is often determined by the aperture of the sensor being used. SAR is able to collect high-resolution images using sensors with a narrow physical aperture. Because SAR is an active remote sensing technology, the radar pulses used by these sensors are also able to pierce dense clouds.

B. Problem Statement

A very peculiar type of distortion is found in images captured using SAR, known as speckle noise. It is a granular noise completely dependent on the signal, inherently found in all synchronised imaging systems that are operational. It also down-samples the image quality in pictorial representation. Speckle severely impacts the performance of automated processing algorithms like scene analysis and information extraction. For these reasons the preprocessing of SAR images aimed at reducing speckles or despeckling has become an active topic of exploration in the scientific community. Contrary to other noises, speckle noise is multiplicative in nature[1]. Therefore, traditional denoising techniques can't be applied over the speckle noise.

As we can see in the above image, adding noise will distort the pixel intensity distribution. And there is less heterogeneity in pixel value as compared to the original input image. As a result of this it is quite hard for algorithms to detect an object, edge or do any operation with images. For these reasons we need to apply despeckling techniques on the images.

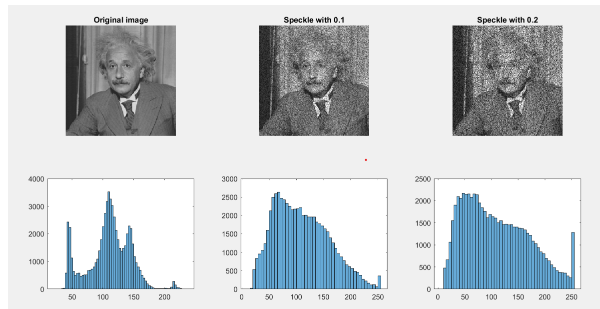


Fig. 1. Histogram of speckle noise and different filters

C. Scope of work

In this project we first analyze the nature and distribution of speckle noise present in SAR images of various bands as well as the effect of various parameters like wavelength, swath and azimuth angle. Further we study the conventional, deep learning and machine learning based approaches proposed till date for reduction of speckles. We will also be implementing a couple of despeckling techniques to see and analyze the results of each of the techniques on the same image. We have also successfully reconstructed the method proposed in [3], and we have further proposed a novel dataset for better training of deep learning models based on scientific evidence.

II. Literature Study

A. Speckle Reduction Techniques

There are 2 traditional categories to reduce the noise[2]. In Spatial Domain iterate a window on all pixels and replace value by some mathematical function. In the transform domain, for noise removal, threshold values are assigned to domain filtering coefficients. A considerable quantity of information is included in a tiny section of the transform coefficients due to the energy compaction feature. These approaches are complicated and lack an appropriate noise model, making it difficult to determine a noise removal threshold. The usual speckle reduction techniques are covered in this section.

1) Lee Filter [3]: The value of the surrounding pixel is used by the Lee filter. The computational cost is very high because each pixel is processed individually. It performs better on homogeneous images (farms) than images with boundaries or lines since it accounts for adjacent pixels (Road detection). It divides three classifications into categories. The value of each pixel is substituted by the corresponding pixels around it.

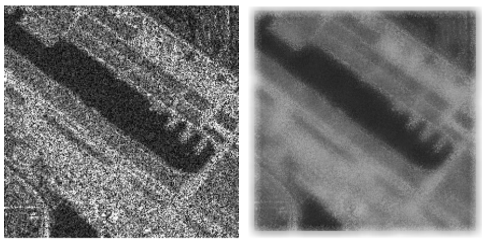


Fig. 2. Noisy image (left) and its corresponding output from filter (right)

2) Kuan filter [4]: This filter is elongated variation of the above mentioned Lee filter. It basically uses the non-stationary mean and variance of the input image. The main aspect of using this filter is despeckling of images based on the corresponding image signal. It generates the signal based on a noise model and then it will apply this to a non-stationary process. This way it will try to reduce noise and it will also preserve sharpness features from the image.

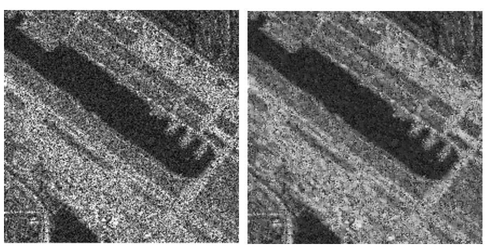


Fig. 3. Noisy image (left) and its corresponding output from filter (right)

3) Frost filter [5]: This type of filter is based on the exponentially-weighted average filter. Here, we use the term damping factor, which basically calculate the distance which is taken from the center of the filter, and the local variance. So, now when we apply this filter to an image, the corresponding value for a particular pixel in the given image is replaced by calculating the damping factor.

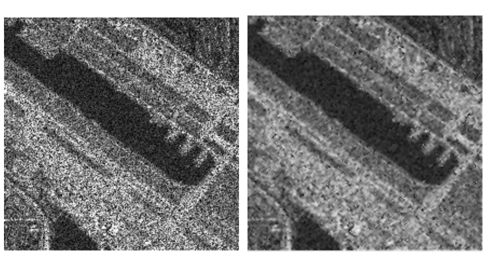


Fig. 4. Noisy image (left) and its corresponding output from filter (right)

4) Gagnon Filter [16]: The basic working of the Gagnon filter is that it will shrink the noisy wavelet coefficients and then it will use the shrinkage rule to reconstruct the filtered image from the original image. This approach has proved to be a very effective way to reduce noise from the noisy image. Alternatively, it also increases the computational effort. The main purpose of using this filter is of the edge detection, and for that a modified ratio edge detector is used. This information is used to maintain edges during the denoising of images.

5) Reduced Gamma map filter [26]: In remote sensing and radar images, the gamma filters are most commonly used because they have to promising to speckle reduction and also to preserve the edges in the images. This type of filter shows similar properties with the Kuan filter, apart from the fact that the data follows the Gamma distribution. During applying this type of filter, the pixel values are replaced by the value which is obtained from the local statistics.

B. Introducing Neural Networks

Considering all the above filters, the most general drawback about using filters for image denoising is that we will not be able to denoise or despeckle an image efficiently because when a filter is applied to an image then it will not be able to get the convolved representation of despeckled image. Here, the basic idea is to remove as much noise as possible from the despeckled image. This can only be possible if we consider a convolved image. Hence, Convolutional Neural Networks have been introduced so that we can go deeper into an image and be able to remove noise from that image. The proposed methods for image despeckling using CNNs are described in this section. This method used a discrete CNN Structure which is used to train the mapping of images. This is done from the input images which is of SAR. The devised approach to this issue is to convert the image into the logarithmic domain and adapt the significant mapping using CNN[20]. This method, however, requires an additional steps to convert the image to a logarithmic domain and back to the original image domain. As a result, the entire process cannot be taught from start to finish. To solve this problem, a division residual approach is applied, in which a noisy SAR picture is regarded a product of cleaned image and noise. We looked at two different network architectures: 1] SAR CNN, 2] ID-CNN and 3] ID-GAN.

C. Network Architecture:

1) SAR-CNN (Synthetic Aparture Radar Convolutional Neural Neworks) [18]: This is the first recommended residual learning-based learning without pooling. There are 17 convolutional layers in this network. Each individual layer receives the feature map having the value 64, with a filter size of 3x3x64. A single layer input and output is employed in the initial and the last levels. The network retrieves the speckled component rather than the clean image. The speckled component is then stripped of the noisy image. The loss function is obtained by using a homomorphic technique along with linked log and exponential transformations to deal with multiplicative noise. Residual learning is a technique for accelerating the learning

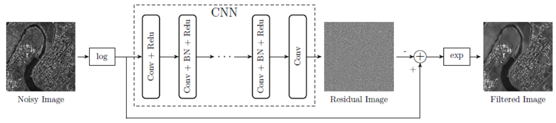


Fig. 5. SAR - CNN Architecture [18]

process. The learning process in CNN is particularly sluggish when the intended output is identical to the input, which is the situation in the restoration process. As a result, training gets faster when the secondary aim of recreating the noise is used.

*2) **ID-CNN (Image Despekling Convolutional Neural Newtorks) [8]**:* To determine speckle noise in SAR images, ID-CNN has been designed. It consists of convolutional layers, activation functions such as rectified linear unit (ReLU), batch normalization, and division residual layer. Now, this network is trained using a loss function. The loss function consists of two components 1.Euclidean loss 2.Total Variation (TV) loss. From a few experiments, it has been shown that the Euclidean loss is much more effective in image restoration problems, so this has been employed in the final estimated image. Hence, the loss algorithm includes an additional TV loss to give more accurate and consistent results. Thus, the loss function consists of Euclidean loss plus Total Variation loss. The ID-CNN noise-detection part has 8 convolutional layers

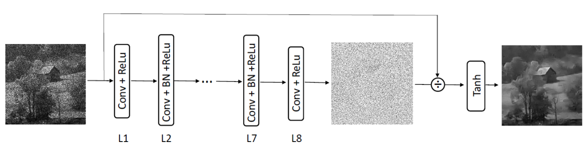
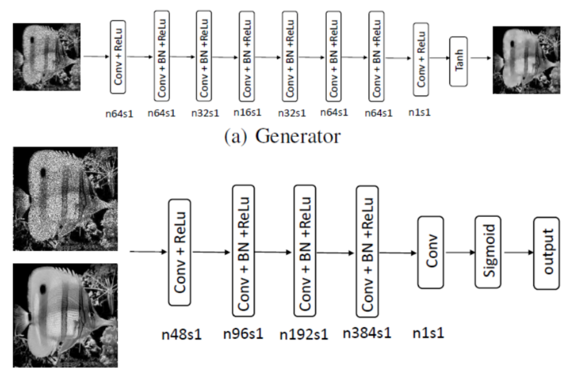


Fig. 6. IDCNN - CNN Architecture [19]

(combined with batch normalization and ReLU function) [18]. It also has zero-padding so that the input image dimensions are exactly the same as the output image dimensions. Apart from the last convolutional layer, all the other layers have 64 filters with stride value of 1. After the convolution process, the input image is splitted by the speckled noise with the help of division residual layer consisting of skip connections. A nonlinear function is created by stacking a hyperbolic tangent layer at the network's conclusion. The details of the network is shown in the below Network Configuration TABLE. Implementing CNNs is not a tedious task. However, there are few limitations in it which are as follows: If we use max pooling as a pooling layer in CNNs then it can be much slower as compared to other layers. CNNs can be time consuming because here we are taking the convolved image. The convolution of images generally requires ample amount of time and large computation.

Convolutional layers require a large dataset to train the network and since our data set is not large enough, we might not be able to accept this network because we can get better results with different networks as well. Hence, state-of-the-art GANs have been introduced in the next section.

*3) **ID-GAN (Image Despeckling Generative Adversarial Networks) [21]**:* In general, the Generative Adversarial Networks (GANs) is the prominent architecture in image based restoration methods in the recent years [21] [22], [23], [24]. The prime motivation of CNN-based approaches for image restoration is to get as much as less value of pixel-by-pixel Euclidean loss. This loss is calculated from the observed image and distorted image. On the other hand, we know that each pixel is handled in similar way and they do no depend on each other, some important data gets removed while encountering the optimum results. Presently, the data getting from the discriminator should be taken care of just to confirm that the denoised image is different from the clean version of the same image. In order to do so, we use Image Despeckling Generative Adversarial Networks which can also be refeed to as ID-GAN.



(a) Generator

(b) Discriminator

Fig. 7. IDGAN - CNN Architecture [19]

The proposed ID-GAN architecture basically has two types of networks or models. One is the generator model and the other is the Discriminator model. Both of these can be referred to as subnetworks. They both consist of several convolutional layers with different activation function and other hyperparameters. The min-max optimization framework[18], which is based on game theory, is used to train both Generator, and Discriminator, at the same time. The objective of this GAN architecture is for the training of generator network so that it can produce samples which might look similar to that of the training distribution. There are three kinds of losses: Euclidean loss, Prepectual loss, the Adversarial loss. Combining all these three losses, the training of the generator is done alongwith addition of appriorate weights. The perpectual loss is generally calculated from the high level features of Generator. This loss is optimized so that is can apprehend some important data. Presently, by including the perpectual loss we can be certain that the despeckled image generates the features which exehibits same charactersitic as that of the original cleaned image.

In case of Image Despeckling, the main reason for using this deep learning based approaches is that the model can adapt different limiting factors for image reconstruction straight from training set instead of depending on some predefined image/filters. Perhaps, this was the initial trial in image despeckling with the help of GANs. The experiments that were conducted on real SAR images and the synthetic SAR images indicates, the former method achieves significant performance in contrast to the previous techniques.

III. Results

In this section we proposed the results for the various architectures that were implemented and will also discuss the performance of each model. We have implemented the results for each filters and different deep learning architectures. For implementing the filters it was simple python function to implement. However, for deep learning architectures such as SAR-CNN, ID-CNN, and ID-GAN, we used kaggle GPU(NVIDIA P100, 16GB 1.3GHz) since it was giving us the results in shortest possible time.

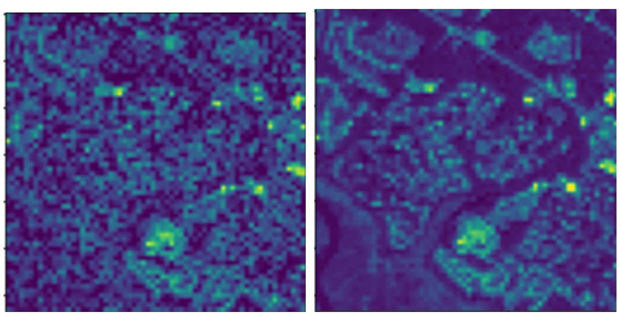


Fig. 8. Noisy image (left) and its corresponding output from SAR-CNN (right)

For ID-CNN (Refer Figure 9), UC Merced data [27] set was used which was taken from European Space Agency (ESA) by registering and creating the account. For SAR-CNN (Refer Figure 8), Sentinel Image Despeckling dataset was used. Lastly, for ID-GAN (Refer Figure 10), the same UC Merced dataset was used.

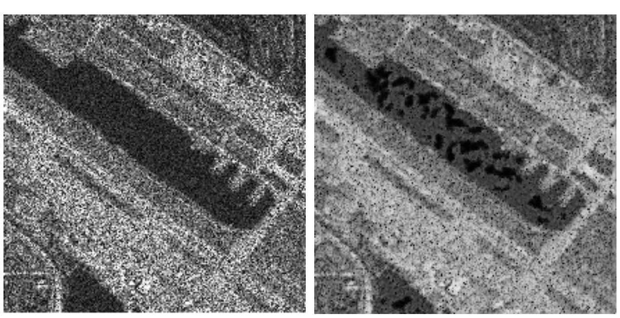


Fig. 9. Noisy image (left) and its corresponding output from ID-CNN (right)

As seen from Table I & Table II, we have calculated two metrics to measure image quality. Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM). They

Fig. 10. Noisy image (left) and its corresponding output from ID-GAN (right)

TABLE I
Comparison of different filter techniques [25]

Metric	Noisy	Lee	Kuan	Frost
SSIM	0.32	0.513	0.592	0.61
PSNR	13	22.15	22.45	23.12
TIME taken (s)	–	0.3	10.8	14.28

TABLE II
Comparison of different CNN techniques [25]

Metric	Noisy	SAR-CNN	ID-CNN	ID-GAN
SSIM	0.32	0.72	0.68	0.76
PSNR	13	25.56	24.45	23.13
TIME taken (s)	–	2.5	0.24	0.67

measure similarity between the output image and the original image. So, basically this PSNR value and SSIM value is directly proportional to the image quality/similarity. The more the PSNR/SSIM value, the high qualified image or similar image will be obtained.

IV. Conclusion

SAR gives important information about earth surface and it is a very efficient method for remote sensing as SAR images can penetrate clouds and work in severe weather conditions. This paper focused different denoising methods for SAR images including deep learning and GAN based techniques. We discussed the results in the above section and from the tables we have a conclusive evidence that SAR-CNN performes better than all other architectures. This can be seen from the PSNR value and the SSIM value. From all traditional despeckling approaches, the proposed architecture shows better performance in speckle reduction. Moreover, these architectures were implemented on kaggle GPU, because of a short run time constraint.

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