COMPARATIVE STUDY OF DENOISING OF SAR IMAGES

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ABSTRACT

SAR images are often tarnished by speckle noise which is multiplicative in nature. Noise makes it difficult to detect objects or any image processing operation. We are discussing analysis and different aspects of multiple despeckling techniques. These include traditional methods, CNN and GAN based techniques.

Index Terms— SAR, Image Processing, Despeckling, CNN, GAN, PSNR.

1. INTRODUCTION

1.1. 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 distance the device travels in the time it takes the microwave pulse to come back to the antenna. Irrespective of the nature of the aperture, the resolution 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 as a result of this. Because SAR is an active remote sensing technology, The radar pulses used by these sensors are also able to pierce dense clouds.

1.2. 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 active coherent imaging systems. It also degrades the images 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 image. Due to this It is difficult for algorithms to detect an object, edge or do any operation with images.

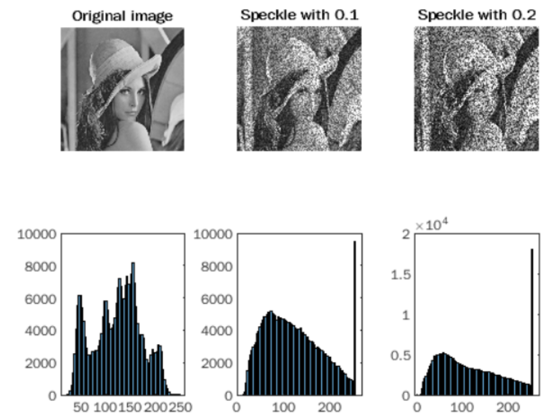


Fig. 1. Histogram of speckle noise and different filters

1.3. 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 traditional, machine learning based and deep learning based approaches proposed till date for reduction of speckles. 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.

2. LITERATURE STUDY

2.1. 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.

Fig. 2. Resulting image after adding speckle noise

2.1.1. *Lee Filter:*

Lee filter uses the value of its surrounding pixel[Lee]. As each pixel is individually processed, Computational cost is very high. As it accounts for surrounding pixels, it works better on homogenous images(farms) rather than images containing edges or lines(Road detection). It assigns categories to three classes. Each pixel is replaced by a value based on the surrounding pixel.

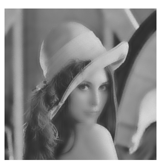


Fig. 3. Resulting image after applying Lee filter

2.1.2. *Kuan filter:*

It is an enhancement of the Lee algorithm. It reduces the noise as well as preserving the sharp edge from the image. It uses non-stationary mean and variance of image model. It generates the signal based on a noise model and then applies non-stationary processes. The key advantage of this method is to reduce noise depending on the image signal.

Fig. 4. Resulting image after applying Kuan filter

2.1.3. *Frost filter:*

It is based on an exponentially-weighted average filter. To replace the pixel being filtered, a value is derived depending on the damping factor, the distance from the center of the filter, and the local variance.

Fig. 5. Resulting image after applying Frost filter

2.1.4. *Refined Gamma Map filter:*

In radar pictures, gamma filters are employed to decrease speckle and preserve edges. The gamma filter exhibits similar characteristics with the Kuan filter, except it assumes that the data follows Gamma distribution. The pixel that is being filtered is replaced with a value derived from local statistics.

2.1.5. *Gagnon Filter:*

It shrinks the noisy wavelet coefficients and reconstructs the filtered picture from them using the shrinkage rule. This approach reduces speckle noise to a greater extent, but it adds to the computational effort. A modified ratio edge detector is used to gather edge information. This information is then utilized to maintain edges during the despeckling process.

2.2. Introducing Deep Learning

To remove speckles from an image, researchers employed statistical approaches such as multilooking [13][14], pixel based filtering [4], wavelet based filtering [12], and so on. Some of these approaches are unable to maintain crisp features and edges because of the fact that the processing is non local in nature, making the work of future processing much more difficult. Deep learning has seen a surge in its use in image restoration and enhancement tasks such as denoising and super-resolution in recent years. Image Despeckling techniques have also beaten the state-of-the-art algorithms in this particular domain. However, the recurrence is bounded because of the insufficient availability of the standard dataset. The main advantage of employing deep learning methodologies for image denoising is that instead of depending on predefined image priors or filters, all deep learning methodologies try to learn and fit various parameters for image restoration straight from the training data.

This section describes the proposed methods for image despeckling using CNNs. In this method train a mapping image from an input SAR image to a despeckle image using a specialized CNN architecture. Transforming the picture into a logarithmic domain and learning the relevant mapping through CNN [20] is one possible solution to this challenge. However, this method necessitates additional steps to convert the picture to a logarithmic domain and back to an original image domain. As a result, the whole method can't be taught from beginning to end. A division residual approach is used in this approach to overcome this issue, in which a noisy SAR picture is considered as a product of cleaned image and noise. We have tried to analyze two network architectures: 1] SAR CNN and 2] ID-CNN.

2.3. Network Architecture:

2.3.1. SAR-CNN (Synthetic Aparture Radar Convolutional Neural Neworks)

This is the first recommended residual learning-based learning without pooling. There are 17 convolutional layers in this network. Each layer receives 64 feature maps with a filter size of 3x3x64. In the first and last levels, a single band input and output are employed. 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 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.

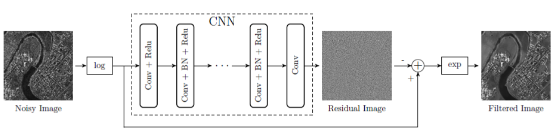


Fig. 6. SAR - CNN Architecture [18]

2.3.2. ID-CNN (Image Despekling Convolutional Neural Newtorks)

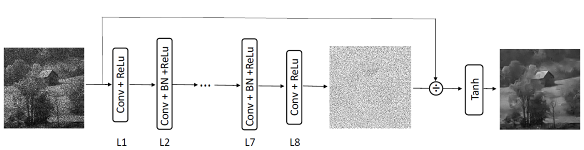


Fig. 7. IDCNN - CNN Architecture [19]

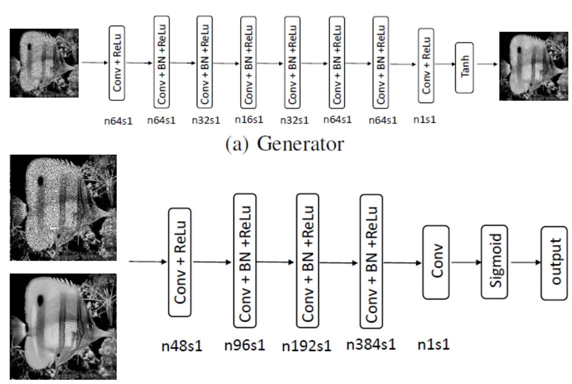
To determine speckle noise in SAR images, ID-CNN has been designed. It consists of convolutional layers, activation functions such as rectified linear unit (ReLU), batch normalization, and division residual layer. Now, this network is trained using a loss function. The loss function consists of two components 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 (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. This convolution of images takes a lot of time and 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.

2.3.3. GAN Based Approaches:

GAN's purpose is to teach G(Generator) to synthesize samples from a training distribution so that the discriminator D can't tell the difference between them and the actual distribution. They are made up of two networks termed a generator and a discriminator that are based on game-theoretic ideas. The generator's goal is to learn a latent space that will allow it to create samples which are similar to training data, whereas the discriminator's goal is to classify whether a particular sample is generated from the generator or taken from the training set.



(a) Generator

(b) Discriminator

Fig. 8. GAN - CNN Architecture [20]

Here, n48s1 means using 48 features and 1 stride, and likewise. Its main purpose is to despeckle a noisy observation and recover a despeckled image. The discriminator subnetwork D separates the de-speckled picture produced by the generator G from the equivalent ground truth image. In other words, it serves as a guide for G. We construct an improved perceptual loss function to solve the issue of GANs being unstable to train, which typically causes artifacts in the output picture synthesized by G. Furthermore, the use of perceptual loss helps ensure that semantically relevant information are preserved in the despeckled findings.

2.3.4. ID-GAN Architecture:

Because the purpose of SAR picture de-speckling is to create pixel-level de-speckled images, the generator should be able to remove speckles as much as feasible while preserving the underlying clean image's detail information. The network uses two types of layers. One is convolutional layer and the other type is de-convolutional layer. Due to this, the designed network is easily able to capture significant image features during the removal of noise with the help of convolutional layers, and then reconstruct image details from features via de-convolutional layers. In terms of the discriminator D, we use the structure provided in [19]. A sigmoid function is layered at the end to convert the output to a probability score normalized to [0, 1].

ID-GAN uses a single feedforward procedure to create the despeckled form of a SAR picture. The network in our technique is meant to minimize the perceived difference between the restored picture and the ground truth image, which is an intriguing characteristic.

3. CONCLUSION

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 reviewed different denoising methods for SAR images including DL and GAN based techniques. Every method has its own benefits and drawbacks.

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