Denoising of SAR Images

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Minor Project

Submitted in fulfillment of the requirements for the degree of

Bachelor of Technology in Information Technology

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CERTIFICATE

This is to certify that the Minor Project titled "Denoising of SAR Images" submitted by SHREY DABHI (16BIT039), UTKARSH PATEL (16BIT083) and KARTAVYA SONI (16BIT087), towards the partial fulfillment of the requirements for the degree of Bachelor of Technology in Information Technology of Nirma University is the record of work carried out by him/her under my supervision and guidance. In my opinion, the submitted work has reached a level required for being accepted for examination.

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ABSTRACT

This work represents the project that aims to develop new models for denoising of satellite imagery and new strategies to train existing state of the art deep learning denoising models. The other outcomes would include, but are not limited to, a new dataset of satellite imagery for better training of deep learning models and improved performance in other similar image processing tasks like super resolution. This project majorly focuses on images captured by Single Aperture Radar due to the peculiar nature of noise present in these images.

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1. Introduction

1.1 SAR Images

Synthetic aperture radar (SAR) is a remote sensing technique that has originated from the domain of side looking airborne radar. SAR sensor are mounted on a moving platform like an aircraft or a spacecraft. The distance the device travels in the time taken by the microwave pulse to return to the antenna creates a large perceived aperture.

Typically, the resolution of the captures image depends on the aperture of the sensor used, regardless of the nature of the aperture. This allows SAR to capture high resolution images using sensors with relatively small physical aperture.

SAR being an active remote sensing technology, it can operate even during night hours. The radar pulses used by these type of sensors also have the ability to penetrate dense cloud cover. Hence, it can be used for monitoring even during bad weather conditions.

1.2 Problem Formulation

A very peculiar type of distortion is found in images captured using SAR, known as speckle noise. It a granular noise completely dependent on the signal, inherently found in all active coherent imaging systems. It also visually degrades the appearance of images. Speckle severely impacts the performance of automated processing algorithms like scene analysis and information extraction. [1] 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.

A steadily increasing number of papers specific on despeckling has appeared in the literature over the last ten years, presumably because the new generation of satellite SAR systems has dramatically raised the attention of researchers in signal processing towards this problem. [1]

As mentioned in [2], speckle noise can be mathematically modelled as:

$$Y = FX,$$

where $Y \in \mathbb{R}^{W \times H}$ is the observed image intensity, $X \in \mathbb{R}^{W \times H}$ is the noise free image, and $F \in \mathbb{R}^{W \times H}$ is the speckle noise, assuming that the SAR image is an average of L looks, the observed image Y is related to X by the above given equation. One common assumption on F is that is follows a gamma distribution with unit means and variance $\frac{1}{L}$ and has the following probability density function:[2]

$$p(F) = \frac{1}{\Gamma(L)} L^L F^{L-1} e^{-LF},$$

Where $\Gamma(\cdot)$ denotes the Gamma function and $F \geq 0, L \geq 1$.

Various methods have been developed in the literature to suppress speckle including multi-look processing, filtering methods, wavelet-based despecking methods, block-matching 3D (BM3D) algorithm and Total Variation (TV) methods.

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. Work Done

2.1 Characteristics of SAR images

The SAR algorithm, as given here, generally applies to phased arrays.

A three-dimensional array (a volume) of scene elements is defined, which will represent the volume of space within which targets exist. Each element of the array is a cubical voxel representing the probability (a "density") of a reflective surface being at that location in space. (Note that two-dimensional SARs are also possible, showing only a top-down view of the target area.)

Initially, the SAR algorithm gives each voxel a density of zero.

Then for each captured waveform, the entire volume is iterated. For a given waveform and voxel, the distance from the position represented by that voxel to the antenna(s) used to capture that waveform is calculated. That distance represents a time delay into the waveform. The sample value at that position in the waveform is then added to the voxel's density value. This represents a possible echo from a target at that position. Note there are several optional approaches here, depending on the precision of the waveform timing, among other things. For example, if phase cannot be accurately determined, only the envelope magnitude (with the help of a Hilbert transform) of the waveform sample might be added to the voxel. If waveform polarization and phase are known and are accurate enough, then these values might be added to a more complex voxel that holds such measurements separately.

After all waveforms have been iterated over all voxels, the basic SAR processing is complete.

What remains, in the simplest approach, is to decide what voxel density value represents a solid object. Voxels whose density is below that threshold are ignored. Note the threshold level chosen must be higher than the peak energy of any single wave, otherwise that wave peak would appear as a sphere (or ellipse, in the case of multistatic operation) of false "density" across the entire volume. Thus to detect a point on a target, there must be at least two different antenna echoes from that point. Consequently, there is a need for large numbers of antenna positions to properly characterize a target.

The voxels that passed the threshold criteria are visualized in 2D or 3D. Optionally, added visual quality can sometimes be had by use of a surface detection algorithm like marching cubes.

2.2 Image quality measures

Various different quality measures were proposed over the years to check the efficiency of denoising techniques. These algorithms check various different parameters like empirical amount of noise present in the image, the structural integrity of the image after removal of noise and the effect of denoising algorithms on the low level features present in the image.

- Root Mean Square Error [5]

  It stands for root mean square error. It measures the average squared difference between the original and cleaned images, where the original and cleaned images have size $X \times Y$ pixels. Accordingly, the RSME is the root of MSE given in the following equations:

$$MSE(I_{filt}, I_{ref}) = \frac{1}{XY}\sum_{i=1}^{Y}\sum_{j=1}^{X}\left(I_{filt}(i,j) - I_{ref}(i,j)\right)^2$$

$$RMSE = \sqrt{MSE}$$

- Peak Signal to Noise Ratio [6]

  PSNR is defined from RMSE. It is the ratio between the possible power of a signal and the power of corrupting noise. For 256 gray levels, PSNR is defined as

$$PSNR = 20\ \log_{10}(\frac{255}{RMSE})$$

- Universal Quality Index [7]

This quality measurement approach does not depend on the images being tested, the viewing conditions or the individual observers. More importantly, it is applicable to various image processing applications and provide meaningful comparison across different types of image distortions.

Let $x = \{x_i | i = 1, 2, \dots, N\}$ and $y = \{y_i | i = 1, 2, \dots, N\}$ be the original and test image signals respectively. The index is defined as

$$Q = \frac{4\, \sigma_{xy} \mu_x \mu_y}{(\sigma_x^2 + \sigma_y^2)(\mu_x^2 + \mu_y^2)}$$

The dynamic range of Q is [-1, 1]

- Structure Similarity Index Measure [8]

  This method quantifies the image quality degradation which is caused by processes such as data compression and loss of information in transmission. It requires two images from the same capture, one of which is the reference image and the other being processed image. SSIM can measure the perceptual difference between the two images but cannot judge which of them is original or of better quality.

- Feature Similarity Index Measure

  This method is based on the principle of HVS (Human vision system) specifically two kinds of features named phase congruency (PC) and gradient magnitude (GM). It is one of the good methods to measure similarity as it is normalized difference between two images.

2.3 Traditional denoising techniques

Several adaptation methods are proposed to achieve a better result by varying window size and also to preserve the features like edges.

- Lee Filter

  This filter is solely based on statistics of window pixels and each pixel is processed individually. This method includes calculating a linear combination of central pixel Intensity of the window with an average of surrounding pixels to suppress speckle noise. The filter is able to suppress the speckle noise but it over smooth the content of an image.

- Frost Filter

This filter is adaptive in nature and uses an optimum minimum MSE filter based on local standard deviation to the local mean for smoothing images. So if the coefficient is high (edge cases) the filter tries to retain pixel's original value and in the general case, it behaves like an average filer. Therefore, it blurs the image.

- Kuan Filter

Kuan filter can be termed as an adaptive Lee filer. This filter can adapt itself to the non-stationary mean, non-stationary variance (NMNV). This filter can deal with various noises and details of the image are not needed. However, it over smooths edges and textures.

- Baraldi Filter

This author proposed Gamma Maximum-Aposterior (RGMAP) method. He came up with a novice idea to construct shape adaptive window near boundaries rather than rectangular boxes. However, this method ignores textures which result in blurred textures.

- Gagnon Filter

Author proposed despeckling method based on symmetric daubechies. It changes the wave of the noise component and recreate the image from it. The logarithmic transformation is done on image and after that it calculates mean and variance. After that inverse logarithmic transforms are performed. This method average results of all WCS filters over all possible shifts of input images. Due to these reasons, Gagnon filter is able to preserve edges of the image. However, It comes at the cost of computation load.

- Chitroub Filter

Author proposed K-distribution to model SAR images. This sampling model is coupled with Monte Carlo technique. The parameter estimation in the paper is quite effective. However, implementation is not so practical.

- Achim Filter

The author came up with an idea to convert multiplicative noise into additive by applying logarithmic transformation.

- Bianchi Filter

The authors proposed an algorithm based on GG distribution. This method is an improvement of locally adaptive GG modelling because expression og GG parameter is derived exactly. However, it comes at the cost of computation due to wavelet transforms.

2.3.1 Experimental Results

Original Image

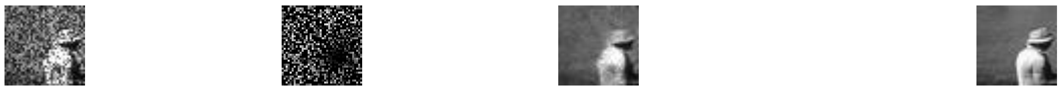
After adding speckle noise

Filter	Image
Lee Filter	
Kuan Filter	
Frost Filter	

2.4 CNN Based Techniques

2.4.1 SAR-CNN

The first proposed residual learning based CNN comprised of 17 convolutional layers, with no pooling. Each layer extracts 64 feature maps using filter size of 3x3x64. The first and last layer has a single band input and output. The network recovers the speckled component of an image rather than the clean image. Then the speckled component is subtracted from the noisy image.

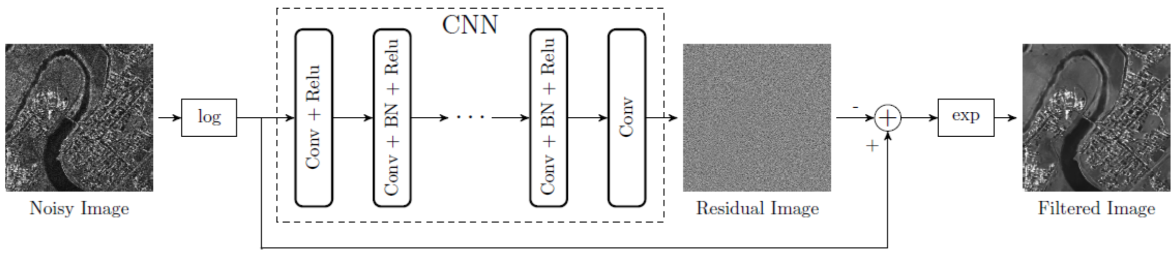


input image ⊕ network output = cleaned image target output

To deal with the multiplicative noise, homomorphic approach along with coupled log and exponential transforms is used, which leads to the loss function.

Residual learning is used to speed up the learning process. It is observed that if the desired output in CNN is similar to the input, the learning process is very slow, which is the case in the restoration process. So by using the dual goal of reproducing the noise, training becomes faster.

CNN architecture:



2.4.2 ID-CNN

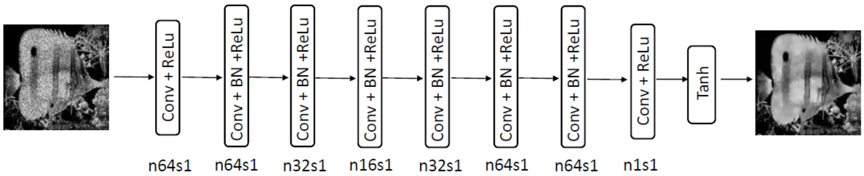
ID-CNN uses a set of convolutional layers along with batch normalization and rectified linear unit (ReLU) activation function and a component-wise division residual layer to estimate speckle and it is trained in an end-to-end fashion using a combination of Euclidean loss and Total Variation (TV) loss.

While the Euclidean loss has shown to work well on many image restoration problems, it often results in various artifacts on the final estimated image. To overcome this issue, an additional TV loss is incorporated into the loss function to encourage more smooth results.

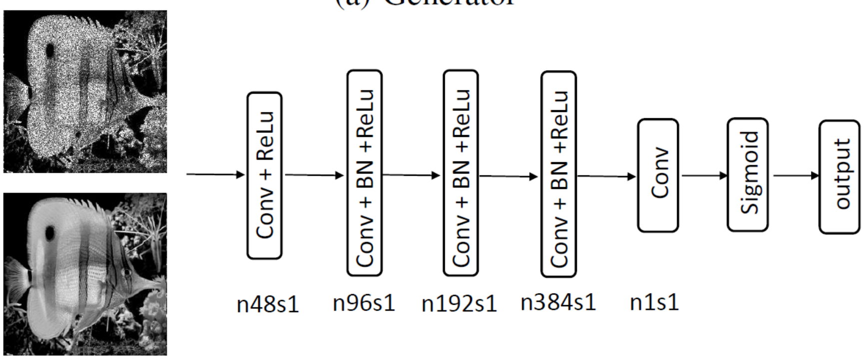
(a) ID-CNN without TV loss (b) ID-CNN with TV loss

2.5 GAN Based Techniques

The authors have proposed a special GAN for generating SAR images to be used in the training process. First, they incorporate the quadratic operation into the GAN, extending the convolution to make the discriminator better represent the SAR data; second, the statistical characteristics of SAR images are integrated into the GAN to make its value function more reasonable; finally, two types of parallel connected GANs are designed, one of which we call PWGAN, combining the Deep Convolutional GAN (DCGAN) and Wasserstein GAN with Gradient Penalty (WGAN-GP) together in the structure, and the other, which we call CNN-PGAN, applying a pre-trained CNN as a discriminator to the parallel GAN. Both PWGAN and CNN-PGAN consist of a number of discriminators and generators according to the number of target categories. Experimental results on the TerraSAR-X single polarization dataset demonstrate the effectiveness of the proposed method.



(a) Generator



(b) Discriminator

2.6 Datasets Available

In SAR image despeckling, the performance assessment is quite challenging, due to the lack of original noiseless signal.

Generally, the strategy has been to train any deep learning model over a set of synthetically generated SAR images, i.e. real world images which have been injected with multiplicative noise.

Different researchers have used different standard datasets for this purpose. For example, the authors of SAR-CNN have used BSD-68 as their base image set, generated crops of 40 x 40 from it, injected the images with multiplicative noise and used it to train their network. The authors of ID-CNN generate a dataset that contains 3665 image pairs. Training images are collected from the UCID, BSD-500 and scraped Google Maps images and the corresponding speckled images are generated using the equation given in the problem formulation section. All images are resized to 256 x 256.

The root cause of this has been the unavailability of large number of pairs of noisy and naturally clean SAR images. SAR images are inherently noisy when captured, and no method proposed till date completely preserves all the important features of the image.

2.7 Curating a New Dataset

We propose a new dataset containing pairs of images from 2 different SAR imaging sensors.

2.7.1 Motivations

From a purely mathematical and scientific point of view, it should be possible to transform an image from a state having higher noise to a state having lower noise. The same algorithm should then be able transform an image already having very less noise to an even cleaner state.

From previous research done, it has already been well established that the amount of speckle noise present in a SAR image is directly proportional to the relationship between roughness of the terrain being scanned and the wavelength of the microwaves being used to scan the region.

A lot of scattering, double bounce and interference occurs when the waves hit the surface if the wavelength of the waves is approximately equal to the roughness of the terrain. There is no standard or even an empirical measure available to evaluate the roughness of the terrain, but we can infer from the visual inspection of the captured SAR image that over a given region if the images have been captured using 2 different sensors, i.e. waves of different wavelengths, which one has a higher amount of noise.

SAR images have a large swath area, and hence are very large in terms of spatial resolution. The point here is that we can use a single SAR image to generate a large dataset of smaller cropped images over which a deep learning model can be trained.

2.7.2 Approach

X - band images from TerraSAR-X are the cleanest images captured by SAR imaging sensor, but they are very expensive and difficult to handle.

Hence, we then identified large repositories of L – band and C – band images. We acquired the C – band images captured during the Sentinel – 1 mission from the public repository being maintained by European Space Agency (ESA). The L – band images are from the ALOS PALSAR mission from the public repository being maintained by Alaska Science Facility (ASF), a subsidiary of NASA. Both of these repos are made freely available for educational and research purposes by the respective organizations.

We then identified a common geographical region over which the images show a significant difference in the amount of speckle noise. This region falls over the southern shores of Hudson Bay, near the border of Ontario and Quebec.

We are currently trying to resolve the issues caused due to the difference in the spatial resolution of level 1 processed product, and are evaluating the pros and cons of using level 0 product (raw single look complex images).

3. Summary and Conclusion

We gained insights into the domain of remote sensing and satellite imagery. We understood and tried to resolve the challenges associated with working on such images. We developed scientific acumen and intuition of working with satellite images.

We understood the problems caused due to noise in any kind of images and its impact on further image processing applications. We studied different types of noise and their nature.

We studied different approaches of denoising and the intuition behind them, as well as their mathematical relevance.

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