Despeckling SAR Images Thought Nest ESA Tool

G. Siva Krishna¹, Shobini.B², N.Prakash³

¹Research scholar, Dept of IT, BSACIST, Chennai, India.
²Associate Professor, Dept of CSE, SITS, Hyderabad, India.
³Associate Professor, Dept of IT, BSACIST, Chennai, India

Corresponding Author: Siva Krishna.G
Email: shivagujju@gmail.com

Abstract

The Synthetic Aperture Radar (SAR) usually corrupted by some surplus speckle formed. These speckles having multiplicative noise, which appears like a grainy pattern in the SAR image. This performs an accurate interpretation of SAR images. The aim of this work was to remove the noise and the accurate classifying the LULC facts with quality evolution with statistical operations. The SAR images to play an import key role on Earth Observation applications using high resolution for all-weather conditions and all times. These Radar satellite collecting images have noise. To despeckle the noise, we propose the NEST Tool. Using this tool we (statistical operations) subtract band wise noisily one. The experiment results are better performance from the state of art techniques.

Keywords: Despeckle learning, SAR, radar, noise, nest tool.

I. Introduction:

SAR images affect with a multiplicative noise, the speckle, which may have several methods to perform basic operations, like classification and segmentation; main aim is to extract useful features form SAR image for end user. Further images are acquiring every day; for this analysis is done regally with some operations, after those operations done every image despeckling a major issue. The number of author’s are has been proposed different approaches in the past few years to suppress the speckle while preserving the most relevant image features [VI, VII]. Wavelet shrinkage [XIX], sparse representations [XX], and especially nonlocal filtering [II, IV, V, III], represent possibly the current state-of-the-art. All approaches are really mentioned in detailed statistical operations of the signal and speckle, either in the original or in a transform domain [I, II]. The speckle removing using CNN (convolutional neural networks) [XI, XII, XIX, XXI, XXII] with a suitable training that is carried out by using multi-temporal SAR images [VIII, IX].
The SAR images are having a top notch deal of speckle noise because of backscattered radar echoes. The state of art phenomenon does not give best deteriorates the picture great, however also makes goal detection, discrimination, and terrain classification tough. The speckle of SAR images collected by different polarization. The SAR Polarizations are two types [X]. The first one, the HH polarization used to horizontal transmission to horizontal receiving, second, the VV polarization used to vertical transmission to vertical receiving. The other combinations also (like as VH, HV) VH image is radar transmits vertically polarized signals then receives the horizontally polarized return signal. HV image is radar transmits horizontally polarized signals but receives vertically polarized signals. These polarizations to consider for calculating LULC facts [XXI, X].

In the process of paper has describe the section propose methodology, then after that experimental results on SAR data, and final section conclusions.

II. Proposed Method

The aim of this approach is despeckling SAR images with statistical operations and filters techniques and compares their result that shown as figure 1. We collect the multitemporal images, firstly remove noise or pre-process the data, then individually process the statistical operations and filter technique, then finally the result compare. The Speckle noise to reduction can be applied either by the spatial filtering or multi-temporal look processing.

![Propose Procedure Diagram]

Speckle filters for handling speckle noise of different distributions (Gaussian, multiplicative or Gamma). The following parameters are select for different techniques; those are source band, speckle filter, kernel width, kernel high, damping factor and edge factor. We did the experiment with SAR images; concentrate on the challenging side-looking multilooking and high-resolution case.

III. Experimental Results

We compare results with speckle filter algorithms, Frost, Lee, Refined Lee, Gamma-Map [X]. For all these above mentioned methods with their parameters are set as suggested in literature papers. The propose method called as despeckling SAR image form mow on, a window size of 2120 X 7850 patches (40 X 40 pixels) is used.
The window-size considering threshold rates 0 to 1 and this experiment carried out in Matlab R2016b and the NEST Tool, with Intel Core at 3.1 GHz.

We are consider the sample subset of SAR images by injecting single-looking the noise in subset image, table 1 reports band wise mean and sigma result for some out of subset images. In these subset images provide the best performance with average over reference techniques of about VH, VV, and HV band wise respectively. Similarly to consider apply for the dB_mean and dB_sigma respectively (table 2). Such result shown as figure 2, with and without despeckling noise.

**Table 1:** Mean and sigma over SAR image

| pixel_no | pixel_x | pixel_y | Intensity_VH_mean | Intensity_VH_sigma |
|----------|---------|---------|-------------------|--------------------|
| 1        | 660     | 273     | 43.8              | 99.9               |
| 2        | 661     | 273     | 45.2              | 29.2               |
| 3        | 662     | 273     | 87.8              | 96.8               |
| 4        | 663     | 273     | 62.8              | 49.8               |
| 5        | 664     | 273     | 31.2              | 65.8               |
| 6        | 665     | 273     | 53.2              | 13.2               |
| 7        | 666     | 273     | 87.1              | 73.9               |
| 8        | 667     | 273     | 13.8              | 84.7               |
| 9        | 668     | 273     | 40.2              | 53.9               |
| 10       | 669     | 273     | 64.5              | 57.1               |
| AVG      |         |         | 52.96             | 62.43              |

**Table 2:** Mean dB and sigma dB over SAR image

| pixel_no | pixel_x | pixel_y | Sigma0_VH_dB_mean | Sigma0_VH_dB_sigma |
|----------|---------|---------|-------------------|--------------------|
| 1        | 650     | 283     | -23.06            | 3.91               |
| 2        | 651     | 283     | -19.65            | 4.68               |
| 3        | 652     | 283     | -18.49            | 4.46               |
| 4        | 653     | 283     | -18.14            | 3.80               |
| 5        | 654     | 283     | -18.60            | 2.98               |
| 6        | 655     | 283     | -16.69            | 4.87               |
| 7        | 656     | 283     | -11.06            | 5.83               |
| 8        | 657     | 283     | -9.30             | 4.31               |
| 9        | 658     | 283     | -10.12            | 6.00               |
| 10       | 659     | 283     | -12.75            | 4.36               |
| AVG      |         |         | -15.78            | 4.52               |
The experiment we consider on SAR images with Multi-temporal filter (MTF) and image size 16000 x 16000 with reprojection. The figure 3 and figure 4 shows result for some of these filters degrade image quality and make interpretation of features more default, and commonly uses for speckle noise reduction technique for a number of $N$ pixels are registered in multi-temporal images, with intensity at position $(x, y)$ in the $k^{th}$ image denoted by $I_k(x, y)$, the multi-temporal filter images are given by equation 1:

$$J_k (x, y) = \frac{E[I_k]}{N} \sum_{i=1}^{N} \frac{I_i(x, y)}{E[I_i]}$$

(1)
for \( k = [1, \ldots, N] \), where \( E[I] \) is the local mean value of pixels in a window size \((x, y)\) in sub select image \( I \). these filter was following two pre-processing steps basically:

a) The first step is calibration in which \( \sigma^3 \) is derived from the digital number at each pixel.

b) The second step is registration of the multitemporal images.

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Figure 3: The result of MTF with (a) repojection, (b) 3 X 3 (c) 5 X 5 (d) 7 X 7 (e) 9 X 9 (f) 11 X 11
IV. Conclusion

The propose paper, we find out the result various multi-temporal filter techniques and statistical operation on SAR image despeckling. A residual techniques are applies, which one is suitable band operation and those operations are performed by MTF in SAR data then it gives the result images. The outcome of both MTF and statistical operation values and images are gives more accurate despeckle the SAR images. Future work these residual approaches are will be considering with image analysis and visual assessment.

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