Intensity SAR Image Denoising with Stochastic Distances Using Non-Local Means Filter

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***Abstract*—Image denoising approaches have attracted many researchers. The main tackled problem is the removal of additive Gaussian noise. However, it is very important to expand the filters capacity to other types of noise, for example the multiplicative noise of SAR images. The state of the art methods in this area work with patch similarity. This paper shows a new approach for speckle removal based on the Non-Local Means filter. The original algorithm was proposed for additive white Gaussian noise (AWGN). We adopt a new approach for the multiplicative noise in SAR images - the speckle noise - using stochastic distances based on the G^0 distribution to compare the similarity of patches, without transforming the data to the logarithm domain, like the homomorphic transformation.**

***Keywords*-intensity image, SAR, speckle noise, multiplicative model, G^0 distribution, stochastic distances, non-local means, denoising**

I. Introduction

The formulation of image denoising methods is a continuing source of interest and still presents many open problems [1]. Most of the methods deal with additive white Gaussian noise (AWGN). However, there is a need to expand the capacity of algorithms to deal with other types of noise.

Advances involving acquisition of SAR images are very important to study surface targets. This type of system is independent of sunlight and climate factors, but the images are contaminated with a multiplicative noise called speckle. It is due to the signal interference with the elements on the surface, and it gives a granulated aspect to the image that complicates its analysis and interpretation.

Recently, the proposed filter by Buades et al [2] applied the patch similarity idea to work with the image redundancy to denoise an image corrupted with AWGN. The similarity between two patches is given by the gray values of the pixels inside each patch. This approach has inspired several researchers to apply non-local denoising algorithms to other types of noise that surpassed many classical techniques.

The work made in [3] improved the performance of NL means and increased the capability to filter the speckle. It is also possible to filter Poisson noise with NL means as demonstrated by [4]. Coupe et al [5] and Guo et al [6] adapted the NL means to reduce the speckle noise of ultrasound images. The research in [7] added the idea of sparsity and dictionary inspired by the NL means algorithm. The BM3D algorithm was proposed in [8]. The performance of this filter surpassed other filters and it is considered the state-of-art by [1]. Its capability was expanded to filter SAR images in [9]. Furthermore, Xue et al [10] applied the cosine integral to NLM, obtaining a filter that is faster than the one proposed in [2] and the speckle noise is well reduced. Zhang and Zhang [11] also filtered SAR images merging the original work by Buades et al [2] with bilateral filtering to detect the targets before the denoising method. Yang and Clausi [12] also elaborated a structure-preserving method to reduce the multiplicative noise. Zhong et al [13] proposed a bayesian method of NL means to work with speckle. Torres et al [14] used the stochastic distances of [15] with the Nagao-Matsuyama filter to despeckling intensity SAR data.

This paper has the objective to demonstrate a new approach with the NL means algorithm using another type of distance: the stochastic distances formulated in [15] using the G^0 distribution of [16]. In this paper we show some preliminary results with this approach and, in a future paper, compare the results with the classical NL means with the homomorphic transformation of [17], BM3D [8], SAR-BM3D [9] and the PPB-Filter [3].

This paper is organized as follows. Section II presents the SAR image model by the G^0 distribution. Section III introduces the stochastic distances. Section IV presents the NL means filter. Section V shows the preliminary results and Section VI presents the conclusions and future research work.

II. Speckle with the G^0 distribution

SAR imagery technique is used to take images of a surface in all weather conditions. There is a coherent processing that generates a multiplicative, signal dependent noise with a granular characteristic called speckle.

A. Multiplicative Model

Considering an intensity SAR image, the return Z is given by

$$Z = X.Y, \tag{1}$$

where X and Y are both independent random variables that represent, respectively, the backscatter return and the speckle.

B. G_i^0 distribution

The work of [16] presents a new distribution for intensity and amplitude SAR images called G^0. The advantage of this distribution is that it models very well the three types of regions present in SAR images: homogeneous, like lakes, rivers and pasture, heterogeneous, like forest and extremely heterogeneous, like cities. We work with intensity SAR image. Therefore, according to [16], the speckle follows a gamma distribution density given by

$$f_Y(y,L) = \frac{L^L}{\Gamma(L)} y^{L-1} \exp(-Ly), y > 0, L \geq 1, \tag{2}$$

where L is the number of looks assumed known and constant. The backscatter return is given by the reciprocal gamma distribution with the density given by:

$$f_X(x,\alpha,\gamma) = \frac{\gamma^{-\alpha}}{\Gamma(-\alpha)} x^{\alpha-1} \exp(-\frac{\gamma}{x}), -\alpha,\gamma,x > 0, \tag{3}$$

where α and γ are, respectively, the roughness and scale parameters. With (2) and (3) it is possible to find the return Z given by the so called G_i^0 distribution:

$$f_Z(z,\alpha,\gamma) = \frac{L^L\Gamma(L-\alpha)}{\gamma^\alpha\Gamma(-\alpha)\Gamma(L)} z^{L-1}(\gamma+Lz)^{\alpha-L}, \tag{4}$$
$$-\alpha,\gamma,z > 0, L \geq 1.$$

III. Stochastic Distances

From the G_i^0 described above and based on the $(h-\phi)-divergence$, the work in [15] displayed eight of the so called Stochastic Distances that were used for hypothesis testing. The purpose of our research is to replace the Euclidean distance of the original NL means filter, that will be described in the next section, for these eight stochastic distances, one at a time, and compare the image filtered with the results of the original NL-means [2], BM3D [8], SAR-BM3D [9] and PPB-Filter [3]. Below are the eight distances - note that the dependence on x of the integrals was omitted:

Kullback-Leibler:

$$d_{KL}(X,Y) = \frac{1}{2}\int (f_X - f_Y)\log\left(\frac{f_X}{f_Y}\right) \tag{5}$$

Rényi order β ($0 < \beta < 1$):

$$d_R^\beta(X,Y) = \frac{1}{\beta-1}\log\left(\frac{\int f_X^\beta f_Y^{1-\beta} + \int f_X^{1-\beta} f_Y^\beta}{2}\right) \tag{6}$$

Hellinger:

$$d_H(X,Y) = 1 - \int \sqrt{f_X f_Y} \tag{7}$$

Bhattacharyya:

$$d_B(X,Y) = -\log\left(\int \sqrt{f_X f_Y}\right) \tag{8}$$

Jensen-Shannon:

$$d_{JS}(X,Y) = \frac{1}{2} \tag{9}$$
$$\left[\int f_X \log\left(\frac{2f_X}{f_Y+f_X}\right) + \int f_Y \log\left(\frac{2f_Y}{f_Y+f_X}\right)\right]$$

Arithmetic-geometric:

$$d_{AG}(X,Y) = \frac{1}{2}\int (f_X+f_Y)\log\left(\frac{f_Y+f_X}{2\sqrt{f_Y f_X}}\right) \tag{10}$$

Triangular:

$$d_T(X,Y) = \int \frac{(f_X-f_Y)^2}{f_X+f_Y} \tag{11}$$

Harmonic-mean:

$$d_{HM}(X,Y) = -\log\left(\int \frac{2f_X f_Y}{f_X+f_Y}\right) \tag{12}$$

In the equations above, X and Y are both random variables in the same probability space and they have the three parameters of G_i^0 the distribution. The α and γ parameters need to be estimated. In our research we follow the suggestion of [15] and we estimated these parameters with the maximum likelihood estimation by the BFGS method.

IV. Non-local means filter

The NL means filter [2] works with the similarity of the patches of a given image. The filter computes a weighted average of the image with the weights calculated by a criterion of similarity, the Euclidean distance, established between the image pixels. The Euclidean distance is computed between a patch of one referenced pixel and other patch centered in another pixel with both pixels inside of a search window. Figure 1 below illustrates the NL means functionality.

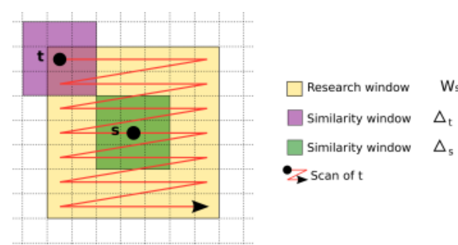

Fig. 1. Functionality of the NL means filter. The yellow window is the NxN search window. The referenced patch is represented by the MxM green window centralized in the s pixel. The purple window represents the patch of a pixel t being evaluated. Figure taken of from Charles Deledalle's homepage at "http://www.math.u-bordeaux1.fr/∼cdeledal/"

Given a corrupted discrete image $v = \{v(i) | i \in I\}$, the estimated value $NL[v](i)$ for an pixel i is computed by

$$NL[v](i) = \sum_{j\in I} w(i,j)v(j), \tag{13}$$

where the weights w are defined by

$$w(i,j) = \frac{1}{Z(i)} e^{\frac{-\|v(N_i)-v(N_j)\|_{2,\alpha}^2}{h^2}}, \tag{14}$$

where $Z(i)$ is a normalizing constant expressed by

$$Z(i) = \sum_j e^{\frac{-\|v(N_i)-v(N_j)\|^2_{2,\alpha}}{h^2}}, \tag{15}$$

and the h parameter acts like a smooth parameter.

V. Preliminary Results

With all the main topics discussed previously, we now detail the goal of our research, as mentioned in Section I. The objective is to replace the Euclidean distance present in the original NL means filter for the stochastic distances to turn the NL means able to filter intensity SAR images contaminated with speckle noise without applying the approximate homomorphic technique.

A. Programming language

The programming language used in this research was R. This language is very useful and powerful when it involves statistical problems. To estimate the α and γ parameters by the maximum likelihood with the BFGS method we used the ”maxLik” package. We set the size of the patches of NL means at $5x5$, because we did not find differences of the estimated values with the usual $7x7$ size. The chosen size of the search window was $11x11$. One of the problems was to set the h parameter of the NL means filter, which is connected with the smoothing performance. We found superior experimental results using very small values for it.

B. Chosen image

The chosen image was the classical $512x512$ ”tank”. To perform the preliminary denoising tests we decide to take a small part of the image. We chose a $50x50$ part of the tank top. After that, we applied an 8 looks speckle noise. Figure 2 illustrates the full image, the chosen part and the zoom contaminated image.

The first stochastic distance used was the Kullback-Leibler distance. We set the patches size at $5x5$ and a $11x11$ search window. We had a difficult step to determine the best value for the h parameter. Experimentally, a small value, $h = 0.055$, was determined.

The first step of the denoising method was to estimate the α and γ parameters of all patches from the image. After that, we applied the filter by replacing the Euclidean distance for the Kullback-Leibler distance. Figure 3 shows the noisy and filtered images.

In a future work we will try to improve the performance of our method and compare its PSNR, MSE, ISNR and SSIM with the listed filters in Section I. Another planned procedure is to apply the method to a larger portion of the image, by improving the computational cost of our approach. Figure 4 below shows the comparison between the histogram of the original image with the filtered histogram. It is possible to note that the maximum, minimum and average values of both images are close. Another point to highlight is the importance of a more formal method to determine the optimal value for h parameter .

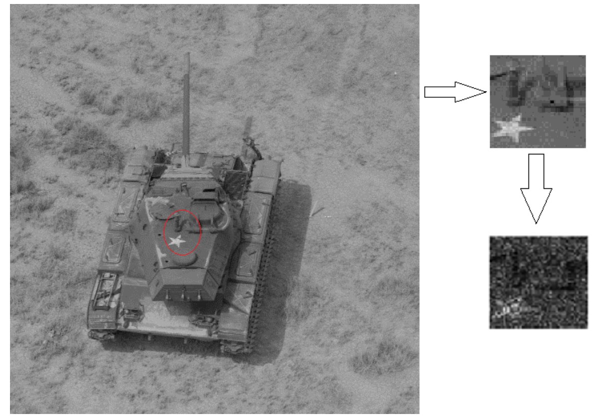

Fig. 2. The chosen image to do the tests. It is a $512x512$ grayscale image and we chose a small part to apply the speckle noise and speed up the process.

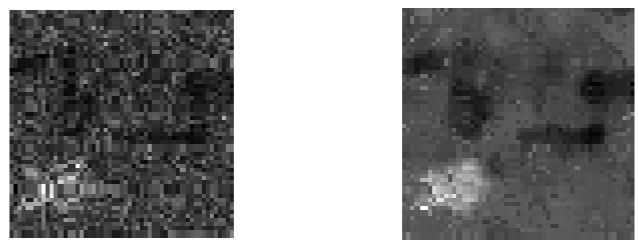

Fig. 3. Comparison between the noisy intensity SAR image (left) and the filtered image (right) with our method.

Figure 4 shows the comparison between the histograms of the original image with the filtered histogram. Figure 5 indicates that the average of the images is quite close and there is a slight decrease of the standard deviation of the filtered image due to the effect of the despeckling method. Tables I and II show the mean, standard deviation, maximum and minimum values of the images. It is possible to observe that tree of these values are close.

TABLE I
Values of the original 50x50 image

Mean	99.74
Standard deviation	24.61
Maximum pixel value	198
Minimum pixel value	27

TABLE II
Values of the filtered 50x50 image

Mean	101.03
Standard deviation	23.78
Maximum pixel value	264.93
Minimum pixel value	30.50

VI. Conclusion and future work

In this paper we show an approach to use the NL means filter to decrease the speckle noise in SAR images by replacing

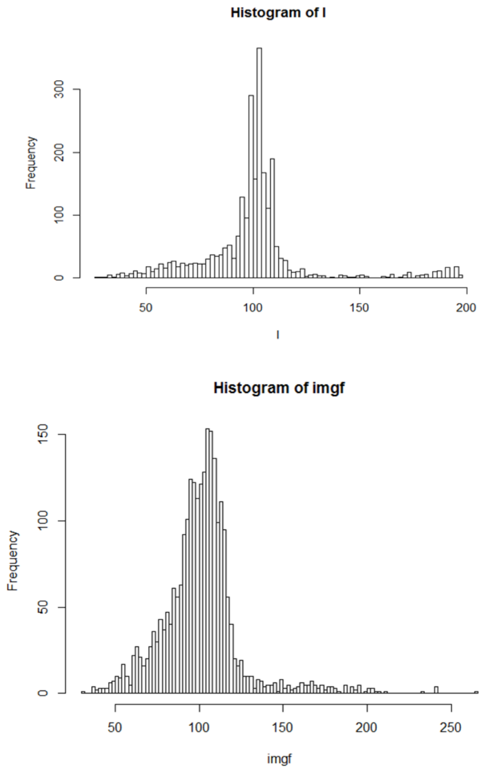

Fig. 4. Comparison between the original $50x50$ image histogram (top) and the filtered image (bottom).

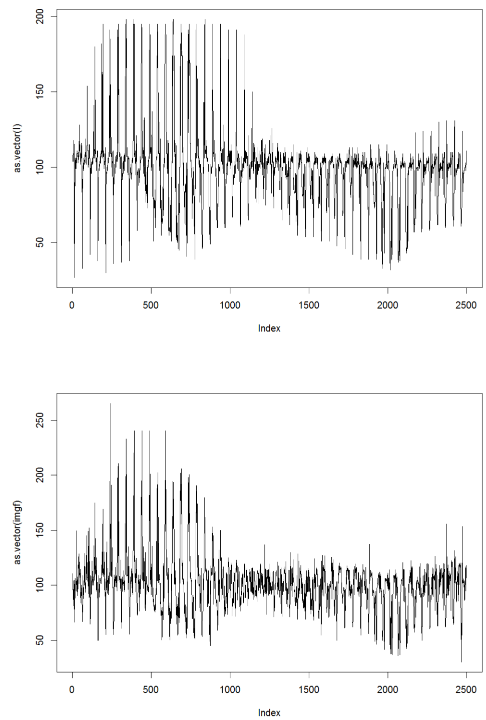

Fig. 5. Comparison between the radiometric forms of the original $50x50$ image (top) and the filtered image (bottom).

the Euclidean distance with the stochastic distances. The first selected stochastic distance for the test was the well known Kullback-Leibler distance. We obtained some improvement in the estimated image compared to the noisy observation, but we still need to refine the process. Furthermore, for a future work, we are working on a method to obtain a pre-smoothed image to get a more accurate estimation of the G_i^0 distribution parameters.

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