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A Performance Analysis of Various Non Local Techniques to Denoise SAR Images

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Abstract: To study surface targets, advances involving acquisition of synthetic aperture radar (SAR) images is important. This 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, non-local approaches have proved very powerful for image de noising. Unlike local filters, the nonlocal (NL) means decreases the noise while preserving resolution. De speckling techniques based on the nonlocal approach provide an excellent performance, but also exhibit a remarkable complexity, unsuitable for time-critical applications. This paper discusses the various techniques used to de speckle SAR images using non local.

Keywords: Synthetic Aperture Radar (SAR), non local (NL) means, de speckling, Block matching 3D

I. INTRODUCTION

Synthetic aperture radar (SAR) image is a 2D or 3D representation of an object in the form of an image. The Synthetic Aperture Radar (SAR) is very useful for providing information about earth's surface by using the relative motion between antenna and its target.

The various application of SAR images include deforestation monitoring, remote sensing, resource monitoring, forest re growth for carbon cycle assessment, oil slick detection, flood prediction, navigation, positioning and military commanding, high-resolution remote sensing for mapping, search and rescue, mine detection, surface surveillance and automatic target recognition, biomass quantification. It possesses numerous advantages over optical satellite imagery; such as, effective operation is achieved irrespective of the weather conditions and can able to penetrate clouds, forest canopy and soil.

Despite of so many applications it is corrupted mostly by signal dependent noise known as speckle noise. Speckle is exactly not a noise but a granular pattern. The returned scattered energy interferes with the returned randomly scattered energy and ultimately introduces speckle noise. The three main aims of Speckle filtering are noise removal in uniform regions, preserving and enhancing edges without changing features, and to provide a good visual appearance.

Research on this topic has been very intense, and many techniques have been proposed based, for example, on adaptive linear filtering, or wavelet shrinkage and, recently, on nonlocal filtering. Traditional de noising techniques using local filtering used to assign the average value of the neighbourhood pixel to the center pixel while de noising this way researcher got nice results if the image was of a homogeneous region, but happen to impair severely the image quality in the presence of fine structures, details, and texture, which are typically over smoothed. Local averaging filters like Gaussian smooth filtering; anisotropic filtering, total variation minimization approach and neighbourhood filtering have their own limitations. Gaussian has the limitation that it is good for flat parts of the image but edges and texture are blurred. The anisotropic filter and total variation minimization approach are preserving edges while flat and textured regions are more degraded. The drawback of neighbourhood filtering is that it compares only gray level values in a single pixel, which is not advisable.The alternative to this local approach is nonlocal–means which is not only compares grey level in a single point but also whole neighbourhood and performs well than local method in terms of method noise, visual quality. The nonlocal approach represents a complete change of perspective since the "true" value of the current pixel is not estimated anymore from the pixels that are closest to it, but from those pixels, located anywhere in the image, which have the most similar context. The above is implemented using finding similar patch; a patch is an area surrounding a pixel. The method uses the center pixel value of the patch to find similar patches. Clearly, this approach is particularly effective on quasi-periodic and textured areas, where repeated patterns abound, but also in the presence of edges and relatively small details.

II. VARIOUS NON LOCAL MEAN TECHNIQUES

Non local approach relies on the observation that most images exhibit clear self similarities, as most patches repeat in an image many times. Once the patches are identified one can apply various de noising techniques to make the image clear.

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In this way we are working for a multipoint filtering rather than point wise filtering.
Block matching 3D (BM3D) algorithm represents the state of the art for images affected by white Gaussian noise (AWGN). In a BM3D algorithm proposed in [2], once a group of similar patches is collected, the whole group is de noised by means of a (3D) wavelet shrinkage process. Then the partially cleaned image is used to estimate the parameters of a further de noising step based on Wiener filtering.
Whereas many recent publications provided new approaches other than the much known BM3D technique to find similar patches and applied de noising filter on this patches to find a noise free image. The results were quite appraising as they provided a reasonable change in the SAR parameters like PSNR value, β -index, SSIM index and other important parameters.

A. BLOCK MATCHING 3D TECHNIQUE (BM3D) (Multipoint approach)

In nonlocal approach, true value of the current pixel is estimated from pixels located anywhere in the images, which have the most similar context.
In BM3D,both context and spatial correlation are taken into account to optimize results .The first action taken in bm3d is to locate similar patches by means of BM(block matching) algorithm with Euclidean metric. All such patches are the collected in 3d structure which undergoes a decor relating transform so as to exploit both spatial and contextual dependencies. Once a sparse representation is obtained, some forms of shrinkage are used to remove noise components, before going back in the image domain. Since filtered patches can overlap, several estimates of the same pixel are typically obtained, and their weighted average must be computed to reconstruct a “basic estimate” of the de noised image. The partially cleaned image is used to estimate the parameters of a further denoising step based on wiener filtering.
Modification is done in BM3D technique because log operation changes the data dynamics and therefore, the distances among patches. As in classic BM3D, the first step is block matching. In BM3D an L2 distance is used to measure block similarity. If the noise variance is low then this kind of measure is robust for an independent additive noise, but if this is not the case, a preliminary thresholding on the block wavelet coefficients can be carried out to reduce noise power before computing block distances, as suggested in [2]. It is clear that we cannot use this strategy on speckled images, so we have changed the measure for block distance as suggested in PPB. After block-matching, modified BM3D stacks similar blocks together to form a 3D array, applies the undecimated wavelet transform, and finally performs shrinkage.
Let z be the observed noisy image and x the noise-free reflectivity (we consider speckle intensity model), hence:

$$\begin{aligned} z(n) &= x(n)u(n) = x(n) + [u(n)-1]x(n) \\ &= x(n) + v(n), \end{aligned}$$

Where u(n) is the speckle that we supposed to be stationary, uncorrelated and independent of x(n). In addition, we assume that E[u(n)] = 1, that is E[u(n) - 1] = 0 which leads us to consider an additive, zero-mean, signal-dependent noise Model, represented in terms of v(n).
In the transform domain the above equation becomes:

$$W_z(n) = W_x(n) + W_v(n),$$

We apply local linear MMSE transform to every detail sub band of the UDWT and then carry out inverse transform $E[W_v^2(n)]$. We reduce the computational burden by assuming E[z2(n)] to be constant in each 3D block, which is quite reasonable considering that they are usually quite small. This choice, together with the use of normalized filters turns into simpler expression

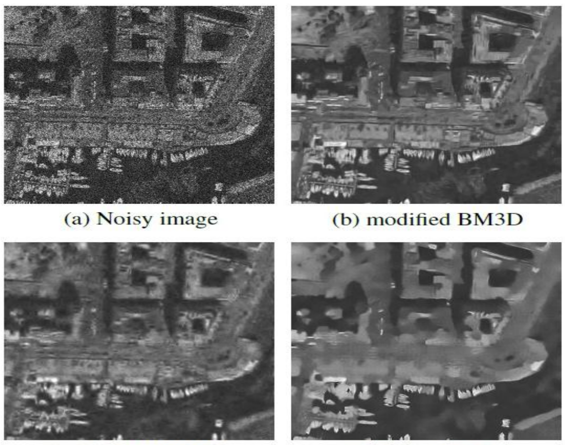
$$E[W_v^2(n)] = \frac{\sigma_u^2}{1+\sigma_u^2} E[z_B^2]$$

Where $E[z_B^2]$ is the mean square value computed on the generic block.
The results are tabulated below:
For Napoli image

TECHNIQUE	L=1	L=2	L=4	L=16
Noisy	14.28	17.05	19.99	25.98
Modified BM3D	23.33	24.92	26.62	30.31
SA-WBMMAE	22.05	23.41	24.78	27.74
PPB SAR 25it	22.01	23.48	25.05	28.07
BM3D	22.89	24.68	26.36	29.98
NLM	21.31	23.65	25.66	28.92
PPB 25it	21.74	23.39	25.07	28.18

Table I: PSNR Results for Test Images with Stimulated Speckle

They took the aerial photograph of the city of Naples, Italy because it has the statistics similar to SAR image. The results were compared from the most recent techniques can be seen in the figure below.



(a) Noisy image (b) modified BM3D
(c) SA-WBMMAE (d) PPB SAR 25it

Fig 1: Experimental Result for Napoli L=1

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B. CLUSTERING APPROACH

In cluster based approach [3] using principal component analysis (PCA) a de noising model is built that represents the multiplicative nature of speckle noise. For solving the PCA- based de noising problem, linear minimum mean square error (LMMSE) approach is used. PCA is a technique that is used for reducing the dataset. In PCA domain the principal component must represent the signal sparsely and it is achieved by performing analysis on similar patches. There are two methods available to find the similar patches and they are Block matching approach and clustering approach.
Block-matching approach finds the pixel or the group of patches that are similar to the reference patch. It is used in BM3D and NLM; however this approach has high computational cost. Clustering approach finds the similar patch by portioning the image also this approach has less computational cost. The clustering based approach uses the K-means algorithm as it is simple and provides high speed however the K-means algorithm also has few limitations such as high dimensionality.
The original SAR image is used to obtain the noisy image and then it is split up into N-sub image patches. Clustering based linear discriminant analysis is performed on the N-sub image patch to obtain the de noised patches of the sub images. Once the noise is removed, these patches are aggregated to form the image. The image is checked for LMMSE and the final de noised image is obtained.

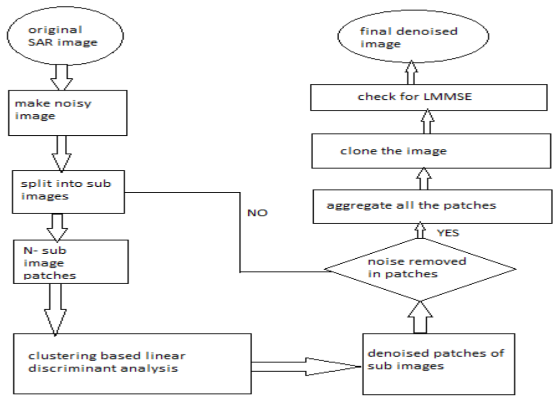

Fig 2: Dataflow Diagram

For the experiment, patch size to 5 × 5 pixels and the sub-images to 64 × 64 pixels, with 5 pixels overlapping with their neighbours are considered and compared the result with the homomorphic approach. The results are as shown in Table I.

The clustering approach can be treated as the unsupervised counterpart of the commonly known to be the block matching technique which requires more computation. So as a future work they proposed the Linear Discriminate analysis (LDA). The primary purpose of LDA is to separate samples of distinct groups. This is done by transforming the data to a different space that is optimal for distinguishing between the classes.

		SAR noisy data set			
		L=1	L=2	L=4	L=16
S/MSE	noisy	6.68	9.35	12.19	18.10
	PPB	14.99	16.56	17.97	21.26
	LPG-PCA	16.70	18.06	19.43	21.15
	SAR-BM3D	14.85	15.04	18.04	21.97
	Prop.	**17.17**	**18.10**	**19.70**	22.24
	Prop.stage1	13.89	15.90	18.67	**22.87**
	Prop.global	12.25	14.04	15.63	20.05
β	noisy	0.183	0.246	0.333	0.572
	PPB	0.323	0.470	0.567	0.696
	LPG-PCA	0.364	0.527	0.658	0.796
	SAR-BM3D	0.484	0.576	0.658	0.804
	Prop.	**0.495**	**0.598**	**0.685**	**0.829**
	Prop.stage1	0.376	0.498	0.616	0.804
	Prop.global	0.321	0.401	0.491	0.687

Table I: Shows the Experimental Results Obtained.

The picture under test is shown below with the final de noised image

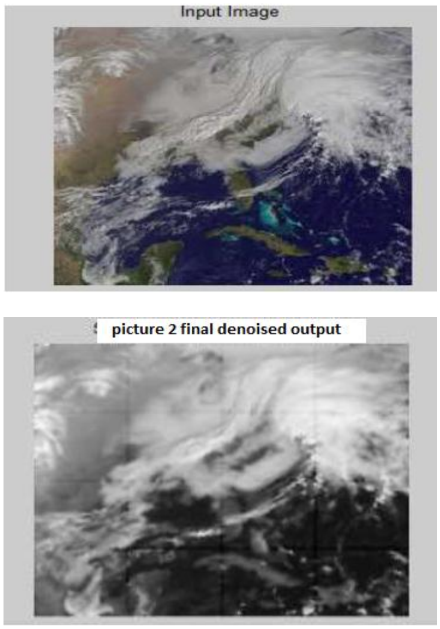

Fig 3: Final De Noised Image by Joining Each Split Sections

C. FAST ADAPTIVE TECHNIQUE

The other approach proposed in [4] is fast adaptive technique using non local means. Processing time in BM3D technique is more so fast adaptive technique is introduced to overcome its disadvantage. The daubechies-4 wavelet in the spatial domain and the haar wavelet have been chosen for fast collaborative filtering. But it causes some performance impairment due to Weiner filtering which is very sensitive to estimation of errors; therefore it has been replaced with wavelet thresholding provided if we are able to estimate local noise variance for each group. With hard thresholding, isolated basis functions stand out in homogeneous areas because of random above threshold coefficients. On the other hand soft thresholding over-smooth important signal features in heterogeneous

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regions. Therefore soft thresholding is used for flat homogeneous blocks and hard thresholding for active ones. For fast/active classification, ratio of arithmetic to geometric means of the observed block intensities is used. In order to preserve relevant image features, the statistic is computed on 16*16 block centered on the 8*8 target block.

The most speed up technique is computing distances only for selected block. Variable-size search area improves performances. Large areas are used for active blocks and small areas for flat ones.

Let dn(x, y) be an additive distance measure between N-vectors and assuming K candidate nearest neighbors (NNs) to x are found already, with T the distance of the farthest. We will update the list of NNs, inserting a new vector y, only if dn(x, y) < T, which requires computing and accumulating N single-letter distances. However, we can stop the computation as soon as the partial sum.

$$d_n(\mathbf{x}, \mathbf{y}) = \sum_{i=1}^{n} d(x_i, y_i), \quad n < N$$

This early termination strategy is very effective with the Euclidean distance because most other candidates are quickly eliminated. Due to log in first pass distance, distance remains small allowing only rarely rapid elimination of a candidate. Variable-search area and probabilistic early termination largely reduce the number of letter-distances to compute, but these are still computationally demanding, so we replace computation with memory accesses. This requires a quantization of the whole image by a suitable NQ-level quantizer Q.

The experiment was performed on 8 × 8-pixel blocks, and a 39 × 39-pixel search area. Fast adaptive non local SAR de speckling (FANS) turns out to be over 10 times faster than SAR-BM3D, comparable to it in terms of both PSNR and SSIM, and superior in terms of β-index, due to the classification step. The experimental results obtained are tabulated below.

	PSNR			SSIM-index			β-index			CPU Time(s)		
	L=1	L=4	L=16	L=1	L=4	L=16	L=1	L=4	L=16	L=1	L=4	L=16
Noisy	12.12 (0.0013)	17.81 (0.014)	23.77 (0.014)	0.120 (0.0005)	0.265 (0.0006)	0.472 (0.0006)	0.070 (0.0013)	0.144 (0.0016)	0.281 (0.0014)			
En-Lee	23.87 (0.037)	28.14 (0.030)	30.64 (0.020)	0.494 (0.0014)	0.704 (0.0011)	0.818 (0.0006)	0.092 (0.0022)	0.247 (0.0026)	0.463 (0.0020)	0.026 (0.005)	0.025 (0.004)	0.023 (0.002)
PPB	26.71 (0.058)	29.84 (0.050)	32.69 (0.032)	0.679 (0.0017)	0.803 (0.0011)	0.876 (0.0006)	0.210 (0.0057)	0.409 (0.0052)	0.566 (0.0031)	182 (0.078)	182 (0.220)	187 (0.099)
SAR-BM3D	27.97 (0.057)	31.20 (0.041)	34.16 (0.028)	0.763 (0.0017)	0.845 (0.0010)	0.899 (0.0005)	0.325 (0.0066)	0.533 (0.0048)	0.681 (0.0024)	94.2 (0.064)	95.8 (0.282)	95.8 (0.288)
FANS-I	26.96 (0.063)	30.76 (0.045)	34.04 (0.030)	0.755 (0.0015)	0.839 (0.0009)	0.893 (0.0005)	0.231 (0.0073)	0.486 (0.0047)	0.683 (0.0018)	2.13 (0.17)	2.42 (0.014)	2.63 (0.007)
FANS-II	27.80 (0.064)	31.33 (0.043)	34.41 (0.026)	0.781 (0.0015)	0.853 (0.0008)	0.899 (0.0005)	0.355 (0.0166)	0.566 (0.0043)	0.704 (0.0018)	6.74 (0.034)	7.24 (0.081)	7.75 (0.015)

Table III: Shows the Experimental Results Obtained.

D. MAXIMUM LIKELIHOOD ESTIMATION

Likelihood Estimation is known to reduce the mean squared error by reducing the variance. The Maximum Likelihood Estimation uses robust m-estimator or Gemam-McMclure estimator for calculating the weight in non-local (NL) means method. The NL means algorithm is based on the redundancy of the neighbouring pixel. The first step in de noising the SAR images using Maximum Likelihood estimation is to calculate the noise standard deviation of the noisy image using data masking technique as noise reduces the possibilities of interpreting the data correctly. To apply the data masking technique the SAR image has to be converted into log domain. The Laplacian mask is used for image structure suppression. Even after applying the laplacian mask there exist some edge structure information. The edge structure information is detected using Sobel edge detector. Using the noise standard deviation it is possible to remove the noise by filtering it. A reference image is created using non-local means which is based on the Markovian hypothesis. The threshold value is calculated using the reference image. A list of pixel values depending upon the neighbourhood noisy pixel value is created for a noisy image. Using this information and the threshold value of the reference image it is possible to detect the pixel that may go to the final noise free image. The pixel value in noisy image and the reference image are obtained and the difference is compared with the threshold value of the reference image. If pixel value is less than threshold value then that pixel from noisy image is selected for de noising using maximum likelihood estimation.

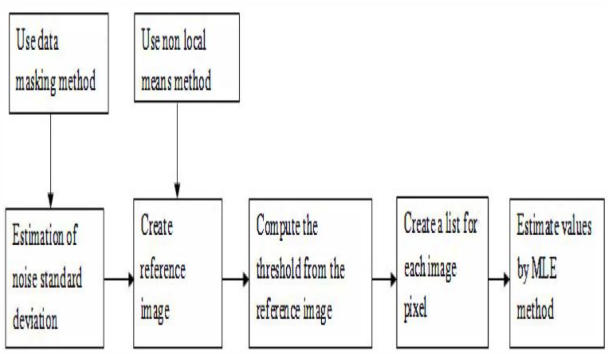

Fig 4: Block Diagram For Denoising

The proposed algorithm was compared with the existing classical NL Means method with a search window size 3x3.

Images	Robust Estimator PSNR Value	NLM PSNR Value
Danube river	73.892	66.3733
Dnieper river	69.5797	56.4047
Mississippi river	70.1493	57.3305
Owens valley	73.6303	62.4473

Table IV: Psnr Values of Proposed Method and NLM Method on Different Images.

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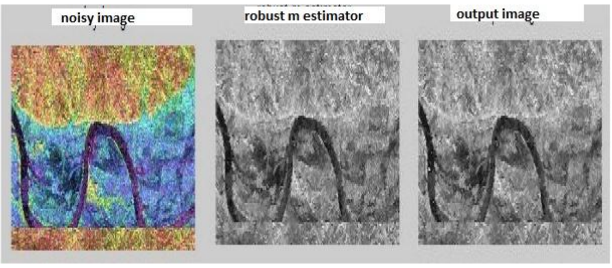

Fig 5: Images Showing the Input Image, the Reference Image Obtained By Robust M Estimator and the Output Image Obtained By Applying Maximum Likelihood Estimation

In all the above stated approaches 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. In [6] the technique adopted to de noise an SAR image using non local means was implemented by using stochastic distances based on the Go distribution to compare the similarity of patches, without transforming the data to the logarithm domain, like the homomorphic transformation. The G0 distribution is a special form of the G model, which can model the speckle fluctuations of many classes of objects present in SAR image like homogeneous, like lakes, rivers and pasture, heterogeneous, like forest and extremely heterogeneous, like cities.

The precise knowledge of the statistical properties of SAR data and backscattering model plays a central role in SAR image processing and understanding. Therefore, statistical modelling of SAR images has become an active research field and numbers of well-known statistical models have been proposed over the past three decades. Currently, most widely used statistical models are developed from the product speckle model, which is based on the assumption that the observed data results from the product between the speckle noise and the terrain backscatter. The G distribution amongst the many statistical models first divides the SAR images scene into homogeneous, heterogeneous and extremely heterogeneous parts according to their homogeneous degrees.

The K and G0 distributions are just the two special forms of the G distribution, where the K distribution is suitable for modelling heterogeneous regions while the G0 distribution is suitable for modelling multi look clutter with widely varying degrees of homogeneity. Compared with the G distribution, the G0 distribution does not involve complex Bessel functions. So the parameter estimation of the G0 distribution is relatively easy, and the computational complexity is low. Consequently, the G0 distribution has become one of the most promising statistical models in recent years.

There are eight stochastic distances which can be calculated using G0 distribution. The eight stochastic distances are stated below:

Kullback-Leibler:

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

Rényi order β $(0 < \beta < 1)$:

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

Hellinger:

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

Bhattacharyya:

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

Jensen-Shannon:

$$d_{JS}(X,Y) = \frac{1}{2}$$

$$\left[\int f_X \log\left(\frac{2f_X}{f_Y + f_X}\right) + \int f_Y \log\left(\frac{2f_Y}{f_Y + f_X}\right)\right]$$

Arithmetic-geometric:

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

Triangular:

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

Harmonic-mean:

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

This paper proposed the use of kullback- leibler distance formula to calculate stochastic distance to replace the Euclidean distance in filtering after finding similar patches. They estimated the parameters using maximum likelihood technique. The image used was 512x512 tank image of which they chose an 5x5 patch size and 11x11 window size of tank top.

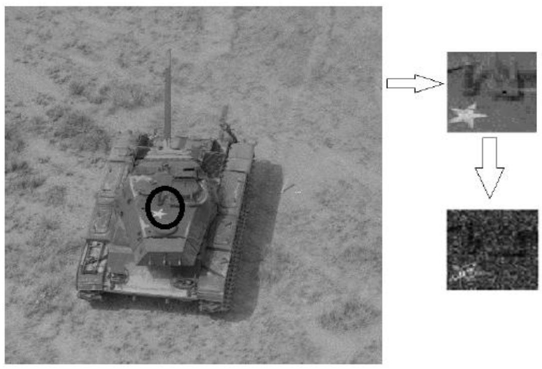

Fig 6 A: A Small Part of the Tank Image Is Added With Speckle Noise

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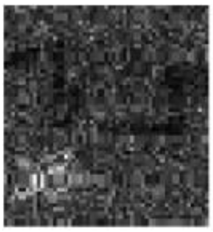

Fig 6 B: Experimental Results of the Sub Part of Tank Image after De Noising

The results are tabulated below:

VALUES OF THE ORIGINAL 50X50 IMAGE

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

VALUES OF THE FILTERED 50X50 IMAGE

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

III. CONCLUSIONS

In this paper we have mainly focused on various de noising techniques applied to SAR images using non local approach. A detailed comparative study of the proposed technique with the previous research is tabulated with each technique discussed. In the modified BM3D technique discussed for L=1 and L=2 values but it decreased for the further values of L. In the cluster based approach a significant improvement can be seen in the mean square error value(S/MSE) and β value for all values of distance L as compared with the basic BM3D technique. In fast adaptive method we can see a reasonable change in the PSNR, SSIM and β index value and CPU time consumed was also less as compared to the basic SAR BM3D, whereas in maximum likelihood estimation they compared the PSNR value for different images with respect to the classic Non local mean techniques used in the past and significant change in figures can be seen as an improvement.

In the last approach discussed was different from the others as in it uses the stochastic distance for finding the patch similarity other then the famous Euclidean distance, they used only the kullback-leibler formula to calculate the stochastic distance a huge increase can be seen in the pixel value from the original noised image and the mean and standard deviation value also increased. If we overall compare all the approach discussed fast adaptive method shows a large difference in values as compared to the under test noisy image in terms of PSNR and β value.

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