

High Density Impulse Noise Removal and Edge Detection in SAR Images based on Frequency and Spatial Domain Filtering

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Abstract — *Development in the science and technology, has been a great improvement in the field of space technology. Now a day's we can even capture the image from the different layers of the earth. This can be referred as Synthetic Aperture Radar (SAR) imaging. As this distance between lens and object increases, it becomes difficult to get the clear and noise-free image. There are many factors which degrade the image in different ways. One such degradation can be in the form of salt and pepper noise. This constitutes for presence of white and black spots on the image. So it is necessary to remove this noise, and to obtain a much clearer image. By taking the advantage of both spatial domain and frequency domain filter, a more effective method of de-noising is proposed. The image is denoised in three folds. First step includes preprocessing by using spatial domain filters, second stage uses frequency domain filter to avoid blurring and smoothing effect on the image. In this stage we use different methods to separate noisy and noiseless pixels, such as any machine learning or deep learning method (ANN, CNN, SVM). Thus maintain the textural information. Last stage uses spatial domain filter to remove any residual noise present. Thus obtained image resembles more with the original image.*

Keywords – Artificial Neural Network (ANN), Support Vector Machine (SVM), Convolutional Neural Network (CNN), Batch Normalization (BN), Rectified Linear Unit (ReLU)

I. INTRODUCTION

The basic principle of SAR imaging is transmitting the electromagnetic waves from moving platform and then receiving the reflected signals (echo) from the target surface using single beam forming antenna. Thus an image of the target surface is reconstructed by processing this echo. The remote sensing devices use their own signals to detect any object. Even the radar can be referred as one of the remote sensing device. The imagining by means of radar is not effected by any environmental conditions such as clouds, rain, day or night. Image can be degraded while acquiring it, or during enhancement or while transmitting it. Coherence problems arise when echo signals are captured by any moving platform. As a result of this problem in synchronization noises will be added to the received images.

Different types of noise that might affect the image are, Speckle noise, additive noise, Gaussian noise etc. Most

important aspect that has to be considered while removing noise from the images is that, the useful information or edges of the images should not be tampered or degraded. The denoising technique should be in such a way, that it has to remove only noisy information, and thus retain necessary information of the image. We require noise free original quality image for enhanced performance and appropriate analysis of the image. Thus the concept of de-noising comes into the picture. De-speckling or de-noising of SAR images has been performed using various methodologies which include both filters and transforms. The Synthetic Aperture Radar (SAR) imaging strategy is prominently utilized for remote detecting and checking applications. In most conditions it is used utilized because of its high usability of use under different climate conditions and furthermore due to its capacity to give high-resolution. SAR image is delivered by sending electromagnetic waves toward the target surface and after that backscattered signals from various appropriated targets. This intelligible handling causes speckle noise and gives SAR image its loud appearance. The nearness of Speckle noise lessens the picture determination and may hamper the task of picture interpretation and examination. Many a people even consider this speckle noise to be same as impulse noise.

The objective of the research is to propose a methodology, that develops an algorithm to remove high density impulse noise from the Input Image, that differentiates between the noisy and noiseless pixels and then performs the required de- noising operation on only noisy pixels, preserve the edge details and also the useful textural and structural information, provide enhanced PSNR value when compared with existing techniques. The proposed work allows de-noising of an image, by making use of the advantages of both frequency and spatial domain filtering and transforming techniques. The spatial domain filtering uses averaging filter, median filter. Frequency domain uses Discrete Wavelet Transform (DWT). In order to separate noisy pixels from noise-less pixels, either of the techniques i.e. Artificial Neural Network (ANN), Support Vector Machine (SVM), Convolutional Neural Networks (CNN) can be used. Organization of this paper as follows , second section gives the literature review of various existing techniques of de- noising of SAR images, third section consists of proposed methodology, and fourth section gives the experimental results, application. Final section consists of conclusion and future scope

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II. LITERATURE REVIEW

The literature review on the SAR images and the existing de-noising techniques will provide us with the base for the objective of this project.

T. Veerakumar [2] proposed a Noise Removal technique utilizing Modified Switching Bilateral Filter. Author proposed this technique to remove impulse noise and improve the details of the image. The proposed filter comprises of two phases. The noise recognition stage depends on the gray level [Lmin, Lmax]. The noise reduction stage depends on the global trimmed mean with modified switching bilateral filter. This strategy adequately removes the high density salt and pepper noise. The simulation results of the proposed filter accomplish high peak signal to noise ratio, image enhancement factor and correlation factor. Time complexity is the major limitation of the proposed method.

Suresh Velaga [3] demonstrated different types of impulse noise removal techniques. The adaptive median filter works better in expelling the salt and pepper noise because of its versatile nature of mask size. The size of the mask depends on the presence of noise quantity in the image. Adaptive Median filter, Frost and Kuan filters, Median filter, Lee filter, DWT and Dual tree Complex Wavelet Transform are considered and their execution is analyzed. The adaptive median filter is additionally compared with other transforms. This method removes high density noise from degraded image.

Manohar Annappa Koli [4] demonstrated a survey of techniques for noise reduction. The work carried out here considers ten powerful noise reduction techniques. The effects of all the calculations are separated and proficiency of calculations is figured. Different images are considered for the purpose of calculation of the results. Different images used are MRI, space, Television images.etc. This overview gives finish learning of noise reduction methods and furthermore, it enables analysts in choosing best motivation to impulse noise reduction algorithm.

R. Sunil [5] proposed an algorithm that is a fusion of both stationary and Discrete wavelet transform for better de-noising. A filtered base analysis will not provide an efficient design metric value, this is observed by Karhunen-Loeve transform (KLT), by comparing the results with Lee and Homomorphic wavelet filters. By performing the above technique, the de-noising ratio is increased at the same time the image resolution is enhanced. All these filtration transforms techniques observed the presence of multiplicative noise in SAR images. The design metric values signal to noise ratio (SNR) and mean square error (MSE) were calculated and plotted.

Pooja Pandey [6] proposed an DWT technique for noise removal. Every current calculation performs well, when the picture show compares to the calculation suspicions, but fails to retain fine structure of images and also creates some artifacts. This paper exhibits a review of some critical work in the territory of picture de-noising. After a concise presentation, some well known methodologies are characterized into various gatherings and an outline of different calculations and investigation is given. Bits of knowledge and potential future patterns in the territory of de-noising are likewise examined.

Alenrex Maity et. all [7], proposed a study on comparison of different techniques of noise reduction. The paper focuses on the comparing different techniques used for speckle noise reduction in SAR images, medical images. Based on soft computing approach, speckle noise is reduced. The results of comparison of performance of various filters showed computed on Lena image showed that, averaging filter and median filter have more PSNR values (i.e. 26.1435db and 24.4083 db) when compared with that of Wiener and Gaussian filters.

Jing Dong et. all [8] proposes a technique to tackle the problem of multiplicative noise by converting it to additive noise model by applying a logarithmic transform. Noise is removed or reduced by using analysis dictionary learning. This method considers logarithmic transform of some patches to form an analysis dictionary. With the help of this dictionary images are restored in log - domain. The proposed method was tested on real SAR images. The method was able to remove the noises, thus preserving the features of image. The drawback of the method as observed from its experimental results is that, the image was smoothened.

Jyoti Sharma et. all [9] proposed an efficient image denoising technique using Neuro fuzzy and SVM. The technique was applied on the medical images. Considering and analyzing the limitations of the previous paper, authors propose an efficient and robust method of noise reduction. It uses both mean and median statistical functions in order to calculate output pixel of training patterns of the neural network and fuzzy logic.

Narayan P. Bhosale [10] proposed a paper which analyses the effect of noise removal filters on the noisy images. The results were observed in the images corrupted by Gaussian noise and salt and pepper noise. The results were discussed by considering an unsharp filter, average filter, wiener filter and median filter. Kai Zhang [24] proposes a deep convolutional neural system for image denoising, where residual learning is used to isolate noise from the image. The batch normalization and residual learning are combined to accelerate the training procedure and also support the denoising execution. Dissimilar to standard discriminative model, which trains the model to a certain noise level, the proposed method models in the general way.

Pre-process the corrupted image using median filter. Also compute the value of PSNR, MSE for comparison purpose.

This pre-processed image is now given to ANN/SVM to separate noisy pixels from noiseless pixels.

III. METHODOLOGY

The section consists of proposed methodology for de-noising of impulse noise in SAR images. In proposed method we are de-noising high density impulse noise present in SAR images using machine learning algorithms. One is Artificial Neural Network (ANN) and the other one is Support Vector Machine (SVM). Denoising can also be performed with the help of deep learning algorithms.



The results of these algorithms are compared; and arrive at the conclusion as to which method is better for de-noising of high density impulse noise in SAR images. The block diagram of proposed methodology is illustrated as shown in the below figure.

Median filter and Averaging filter are spatial domain filters. Direct manipulation of pixels by using mask or window is done in spatial domain filtering. The advantage of using spatial domain filtering is that it is, good for contrast enhancement and image sharpening. The disadvantage is that during sharpening boundaries shifts. No frequency information is achieved. Before the actual process starts, the data set consisting of sample images has to be trained and classified. This can be done using any Machine learning algorithm or even we can use Deep learning for this purpose. This basically differentiates noisy pixels from noiseless pixels; thus help in easy application of de-noising technique to the image.

Proposed scheme works in three stages. The first stage wherein pre-processing of the degraded images takes place. Here the image is passed through the Median filter; some part of degradation is removed in this part. This type of filtering doesn't differentiate between noisy and noise-free pixels. Thus median filtering is applied on all the pixels of the image. The second stage involves ANN / SVM, the deep learning technique where the noisy pixels are separated from noise-free pixels, and on these noisy pixels DWT based denoiser is applied. This stage again reduces some part of impulse noise. During the final stage, the output of previous stage is again passed through ANN / SVM to detect residual impulses. These residual impulses are replaced with the averaged values of its neighboring noise-free pixels.

1. Consider the test SAR image be it a color or grayscale.
2. If the test image is a color image then convert it to a grayscale, else retain the image.
3. Add impulse noise of required noise density.

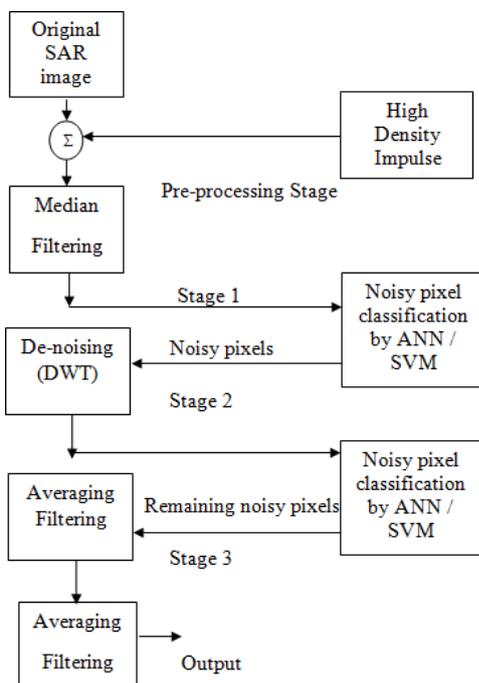


Fig.1. Block diagram of proposed methodology

A. ANN Impulse Detection

Consider a test pixel $O_{i,j}$, from the corrupted SAR image. Consider the test window including the 3 x 3 neighbors of $O_{i,j}$.

The test window will have the elements =

$$\begin{bmatrix} O_{i-1,j-1} & O_{i-1,j} & O_{i-1,j+1} \\ O_{i,j-1} & O_{i,j} & O_{i,j+1} \\ O_{i+1,j-1} & O_{i+1,j} & O_{i+1,j+1} \end{bmatrix} \quad (1)$$

Δ_i

Compute Δ_i 's using the elements of above matrix. It's given by,

$$\begin{aligned} \Delta_1 &= (O + O_{i+1,j+1}) / (2 - O_{i,j}) \\ \Delta_2 &= (O_{i+1,j-1} + O_{i-1,j+1}) / (2 - O_{i,j}) \\ \Delta_3 &= (O_{i,j-1} + O_{i,j+1}) / (2 - O_{i,j}) \\ \Delta_4 &= (O_{i-1,j} + O_{i+1,j}) / (2 - O_{i,j}) \end{aligned} \quad (2)$$

For an artificial neural network are given as the input, and an output is obtained. $Y_{i,j}$ is compared with that of test pixel, and based on the output it is concluded whether the test pixel is corrupted or not.

$$O_{i,j} = \begin{cases} \text{corrupted,} & \text{if } Y_{i,j} \text{ has high value} \\ \text{Not corrupted,} & \text{if } Y_{i,j} \text{ has low value} \end{cases} \quad (3)$$

For binary decision of impulse, is passed through hard thresholding producing output $V_{i,j}$

$$V_{i,j} = \begin{cases} 0, & Y_{i,j} > T \\ 1, & \text{otherwise} \end{cases} \quad (4)$$

where T = Threshold value, and if $V_{i,j}$ is zero, filtering process is initiated.

Shift the window column wise, and then row wise and keep repeating from step 1 to complete the diagnosis of entire image.

All the noisy pixels are collected in an array, and then it is given for DWT based denoiser.

B. DWT based De-noiser

Compute the wavelet coefficients 'detail' and 'approximation' components from the sample data. The detail component consists of high frequency useful components of image and approximation part consists of low frequency information. This mostly constitutes to the noise information. For denoising Threshold Parameter (TP) is set for all coefficients.

$$TP = \begin{cases} 0, & \text{if } |C_{i,j}| > t \\ \text{sign}(C_{i,j})(|C_{i,j}| - t), & \text{if } |C_{i,j}| < t \end{cases} \quad (5)$$

where, $C_{i,j}$ = wavelet co-efficient.

In this method the noise components are threshold to certain level depending upon the threshold factor.

After performing the thresholding compute inverse DWT.

Now the remaining noisy pixels are filtered out using Averaging filter.

Again pass this de-noised image through ANN/ SVM for separating noisy and noiseless pixels.

C. Averaging Filter

$O_{i,j}$ is replaced by the average value of neighboring pixels.



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$$o_{i,j} = (o_{i-1,j-1} + o_{i-1,j} + o_{i-1,j+1} + o_{i,j+1}) / 4 \quad (6)$$

Set every one of $D_{i-1,j-1}, D_{i-1,j}, D_{i-1,j+1}, D_{i,j-1}$ to 1 for the now shifted areas.

Send the Δ_i of test windows relating to the test pixels $o_{i-1,j-1}, o_{i-1,j}, o_{i-1,j+1}$, and $o_{i,j+1}$ through the ANN detector to create $P_{i-1,j-1}, P_{i-1,j}, P_{i-1,j+1}, P_{i,j-1}$

Pass the yield Os' through one of the thresholding technique to compute $D_{i-1,j-1}, D_{i-1,j}, D_{i-1,j+1}, D_{i,j-1}$

Supplant by the normal of the solid pixels as:

$$o_{i,j} = \frac{\sum_{i=1}^3 \sum_{j=1}^3 D_{ij}}{\sum_{i=1}^3 \sum_{j=1}^3 1} \quad (7)$$

C. Deep CNN

Size of convolution filters is 3x3, but in general defined as $(2t+1) \times (2t+1)$ where 't' is depth of layers. High noise corresponds to larger patch size, so that restoration is image information is done easily. Suppose image is of form $y = x + v$, then in residual learning first residual of y close to noise v is approximated, i.e. $R\{y\} \equiv v$ and then original signal is estimated by subtracting it.

$$x = y - R\{y\} \quad (8)$$

There are three layers Conv+ReLU, Conv+BN+ReLU and Conv. Consider the number of layers in DnCNN to be D. First layer Conv+ReLU has 64 filters, with each filter sized as $3 \times 3 \times i$, where 'i' represents number of image channels. The number of second type layer (Conv+BN+ReLU) be 2 to (D-1). Here 64 filters each of $3 \times 3 \times 64$ size are considered. Last layer (Conv) has c filters each with a size of $3 \times 3 \times 64$.

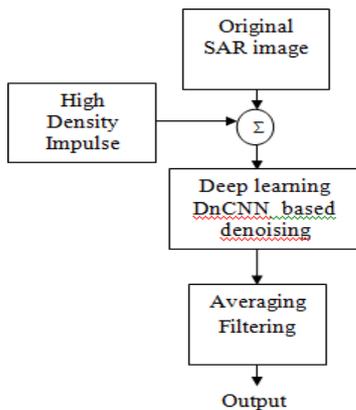


Fig. 2. Block diagram of proposed methodology using CNN

D. Software Requirements

32 bit for MATLAB, and 64-bit for Tensorflow to run python. MATLAB which has inbuilt packages for neural networks should be used. Minimum of 6GB RAM.

IV. EXPERIMENTAL RESULTS

Performance of proposed methodology can be evaluated by various parameters. Comparison of proposed methodology with existing methodologies is made. Some of the parameters of evaluation are,

A. Mean Square Error (MSE) – MSE is a measure of how close a fitted line is to information points. Smaller value of MSE, represents closer the fit to the data.

$$MSE = \frac{\sum_{i=0}^p \sum_{j=0}^p (X_{ij} - R_{ij})^2}{(M * N)} \quad (8)$$

X - Original Image

R - Restored Image

P = M x N - Size of Image

The value of MSE nearer to zero is more accurate

B. Peak Signal to Noise Ratio (PSNR) – PSNR is a term that determines the ratio between the maximum possible power of a signal and the power of corrupting noise. Higher value of PSNR represents better image quality.

$$PSNR = 20 * \log_{10}(255 / RMSE) \quad (9)$$

$$RMSE = \sqrt{MSE} \quad (10)$$

PSNR esteem high means great quality and low means awful quality. PSNR is using a term mean square Error (MSE) in the denominator. Thus, low the error, high will be the PSNR.

C. Percentage of Spoiled Pixels (POSP) - It is the measure of the number of unaffected original pixels replaced with a different gray value after filtering i.e.

$$PSP = \left(\frac{\text{No. of original pixels changing their grayscale}}{\text{No. of non-noisy pixels}} \right) \times 100 \quad (11)$$

Lower value of POSP represents better performance of the detector. Higher value of POSP represents losing of image properties from original image and the presence of edge jitters in restored images.

D. Structural Similarity Index (SSIM) - Structural similarity (SSIM) index method measures the similarity between two images. The SSIM index is calculated on various window size of an image. The measure between two windows of same size $N \times N$.

$$SSIM = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \quad (12)$$

Where

μ_x, μ_y are average of y and x.

σ_x^2, σ_y^2 are variance of x and y

σ_{xy} is co-variance of x and y

$c_1 = (k_1 L)^2$ $c_2 = (k_2 L)^2$

two variables to

stabilize the division with weak denominator

L is dynamic range of pixel values

$k_1 = 0.001$ and $k_2 = 0.003$ default

The resultant SSIM index should be a decimal value ranging between -1 and 1. Value 1 denotes two similar sets of data. Typically $N = 8$.

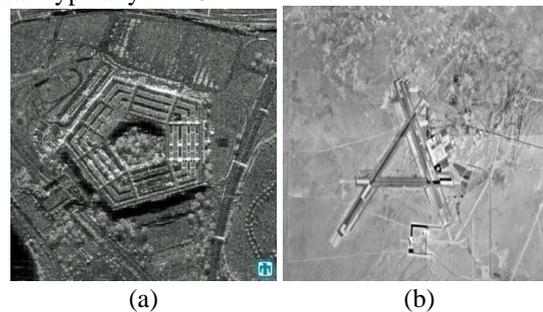


Fig. 3. Original SAR image without noise, Pentagon (a), Chinalake (b)

Results are computed for various noise densities, on different types of SAR images. The number of hidden layers considered in the entire above test is 10. This number can be increased.



The number of training set considered is 48. For different data sets results are tabulated as shown below,

Results for different noise densities:

Data set No.1: Pentagon SAR image

Noisy image	Median filtered image	Output image
Noise Density = 0.2	PSNR =43.9443 MSE =0.0252 SSIM=0.6039 PSP =83.1421	PSNR =55.5809 MSE =0.0066 SSIM=0.92101 PSP =21.8384
Noise Density = 0.4	PSNR =34.548 MSE =0.0743 SSIM=0.39802 PSP =85.3271	PSNR =47.4184 MSE =0.01689 SSIM=0.80095 PSP =41.1011
Noise Density = 0.6	PSNR =24.317 MSE =0.2414 SSIM=0.16278 PSP =88.8062	PSNR =42.3423 MSE =0.0303 SSIM=0.63253 PSP =59.5337

Data set No 2: China lake image

Noisy Image	Median Filtered Image	Output Image
Noise Density = 0.2	PSNR = 34.1269 MSE = 0.07803 SSIM = 0.49502 PSP = 84.1187	PSNR = 63.2607 MSE = 0.00272 SSIM = 0.94076 PSP = 21.0815
Noise Density = 0.4	PSNR = 34.4833 MSE = 0.0749 SSIM = 0.3758 PSP = 83.2581	PSNR = 54.7744 MSE = 0.00724 SSIM = 0.84211 PSP = 40.2466
Noise Density = 0.6	PSNR =24.7473 MSE =0.2297 SSIM=0.10323 PSP =87.1826	PSNR =48.6364 MSE =0.0146 SSIM=0.70314 PSP =58.2397

Data set No 3: Random SAR image

Noisy Image	Median Filtered Image	Output Image
Noise Density= 0.2	PSNR =44.9632 MSE =0.0224 SSIM=0.73019 PSP =80.603	PSNR =55.9784 MSE =0.006305 SSIM=0.93923 PSP =21.6187
Noise Density = 0.4	PSNR =34.3172 MSE =0.0763 SSIM=0.49997 PSP =84.2407	PSNR =47.7271 MSE =0.0163 SSIM=0.8389 PSP =40.5884
Noise Density = 0.6	PSNR =34.1269 MSE =0.07803 SSIM =0.49502 PSP =84.1187	PSNR =48.1109 MSE =0.01559 SSIM =0.82891 PSP =40.8569

Noisy Image	Median Filtered Image	Output image
Noise Density = 0.2	PSNR =51.1142 MSE =0.011 SSIM=0.69654 PSP =80.5359	PSNR =63.4212 MSE =0.00267 SSIM=0.93933 PSP =21.0693
Noise Density = 0.4	PSNR =36.0629 MSE =0.06244 SSIM=0.39233 PSP =83.3252	PSNR =56.6612 MSE =0.00582 SSIM=0.84846 PSP =39.5813
Noise Density = 0.6	PSNR =24.5396 MSE =0.23533 SSIM=0.11878 PSP =87.4329	PSNR =50.5359 MSE =0.0117 SSIM=0.70638 PSP =58.6731

Data set No. 4: Cg University image

This number has to be larger, Because of the memory constraint in CPU, less number of training set are utilized. Typical PSNR values for 8-bit image ranges from 30db to 50 db. For 16-bit, typical PSNR value ranges from 60db to 80db. PSNR values for Deep CNN for a noise variance of 15, varies in the range of 30-32db. For noise variance of 25, PSNR value varies between 29- 31db, and for noise variance equal to 50, PSNR value ranges between 25-29db.

Table.1. Below table gives the comparison of different parameters after de-noising for Pentagon SAR image.

Input SAR Image	Metric	Stationary Wavelet Transform	Homomorphic Wavelet Filter	Curvelet Transform	ANN + DWT (Proposed)	SVM + DWT (Proposed)
Pentagon	PSNR(db)	23.3219	44.9565	33.832	47.1137	45.464
	MSE	1.1914	0.0902	27.094	0.0177	0.0211
Chinalake	PSNR(db)	23.0114	45.5779	-	55.4791	49.691
	MSE	1.2797	0.0840	-	0.0072	0.0101

Table.2. Below table shows the parameter comparisons of proposed scheme with different schemes

Parameters	Noise Density	PSNR (db)	MSE	SSIM	PSP
ANN	0.2	55.5809	0.0066	0.92101	21.8384
		50.0116	0.012534	0.91403	99.5483
ANN	0.4	47.4184	0.01689	0.80095	41.1011
		45.4645	0.02115	0.80023	99.1348
ANN	0.6	42.3423	0.0303	0.63253	59.5337
		41.0378	0.035219	0.62938	98.9075

V. APPLICATIONS

SAR images find applications in various fields, such as pollution monitoring, detection of mines, surface surveillance, automatic target recognition and internal coast wave detection. Most of the man-made unlawful or unintentional works are significantly obvious in radar pictures.



Trademark spillage from oil stores can also be watched. In shallow waters SAR symbolism empowers one to reason the base topography. At high latitudes, SAR information is extremely helpful for provincial ice checking. The property of SAR to enter cloudy cover makes it particularly imperative in regularly shady districts.

VI. CONCLUSION AND FUTURE SCOPE

The proposed method uses three stages for de-noising. Early stage includes pre-processing using spatial domain Median filtering. When image is affected with high density of noise, only median filtering cannot remove the complete noise. Therefore we go for further stages of de-noising. Further stages include detection of noisy pixels from the noisy SAR image. Accuracy of the ANN is more, but it takes more training time. The training time is not fixed, it varies every time. For de-noising in the second stage, frequency domain transform namely DWT is used. In this stage the result is improved by very less quantity. Final stage includes applying Averaging filter on the noisy pixels.

The estimate parameters such as PSNR, MSE will have different values for different noise variance and also for different type of SAR image i.e. whether the image has more detailed information, whether the image is brighter or darker etc. In the future work, instead of using three stages for noise removal, a new technique can be proposed where it'll consider only one stage of de-noising, with the improved results.

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