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# Speckle Noise Reduction in SAR Images using Neuro-Fuzzy Approach

S. Vijayakumar and V. Santhi
*School of Computer Science and Engineering, VIT University, Velllore, India*

**Key words:** SAR image, speckle noise, fuzzy logic system, artificial neural network approach, noise reduction

**Corresponding Author:**
S. Vijayakumar
*School of Computer Science and Engineering, VIT University, Vellore, India*

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**Abstract:** In remote sensing applications SAR images play a vital role. But due to interference in signal, SAR images are getting with speckle noise to greater extent. Speckle noise is a kind of noise that gets multiplied with pixel intensities. Thus, the speckle noise is called multiplicative noise. In this study, computational intelligence based noise removal approach is proposed to remove speckle noise by preserving edges and texture information. The proposed system uses Neuro-Fuzzy approach using basic topology rather using all possible topology to reduce complexity. The performance of the proposed system is measures through objective metrics which shows the efficiency of the proposed approach for noise removal.

## INTRODUCTION

In remote sensing applications, SAR images play a major role due to advancements in image processing technologies and availability of variety of sensors[1,2]. But, the inherent presents of speckle noise in SAR images prevents users from analysing and extracting useful features from it. Thus, the process of removing speckle noise is considered as important task in SAR image analysis and it is called pre-processing[3]. Noise in images is unwanted presence of variations of color or brightness that does not exist in the object of interest[4, 5]. Noise interferes with the original signal and degrades the image quality which results in variations of intensity value which must be removed for retrieval of original image. There are two kinds of noise models based on the way it affects pixel intensity values in images, they are additive models and multiplicative models. Speckle noise is a multiplicative noise model. Additive noise could usually be removed using various linear averaging filters, however, the filters are not as effective at preserving edges as the image is blurred. The edge preserving filters on the other hand might end up amplifying noise. Multiplicative noise is usually dealt with by being transformed into an additive model. In general, noise removal could be carried out using traditional filtering approaches but in recent days researchers have showed attention in using computational approaches for noise removal as presented[3]. In particular, fuzzy logic technique is predominantly used to remove noise as it is uncertain in nature as outlined from[6, 7]. The effectiveness of noise removal approach could be further increased by using Neuro-Fuzzy approaches.

**Literature review:** In this study, a review of related work has been carried out and presented. As per review many filtering techniques are existing includes using artificial neural networks and fuzzy logic techniques for noise removal. But it is important to design new approaches is to preserve textual information and edges. In Russo and Ramponi[8], the Fuzzy Inference filter operator (FIRE) is developed for the removal of impulse noise on digital images. It is designed based on fuzzy inference system which adopts fuzzy rules to remove noise from images and it is a non-linear operator. The main advantage of FIRE filter operator is to remove noise without degrading the quality by preserving fine details and textual information.

Similarly[9] proposed a simple Neuro-Fuzzy operator using fuzzy logic theory to remove impulse noise from corrupted images. The proposed filter uses adaptive Neuro-Fuzzy approach with first order Sugeno type fuzzy inference system. The filtering operation is performed by taking three inputs and produces single output and membership functions considered is generalized bell type distribution as it increases the performance while varying the image properties and the density of the corrupting noise.

By Schulte *et al*.[10] proposed a hybrid model to remove impulse noise from color images using fuzzy logic operations. The main objective of this proposed approach is to enhance edges and texture pixels while removing impulse noise using vector based operations. In general, fuzzy noise reduction approach performs filtering operation between centre pixel and its neighbourhood but in this proposal it is performed by correcting each color component. But noise reduction is carried out on grayscale image by separating each color component.

ByLiang *et al*.[11], an approach is proposed for removal of impulse noise in neural networks environment. It has two stages; in first stage noise is removed using the adaptive two-level Feedforward Neural Network (FNN) with backpropagation algorithm. In second stage, image pixels are classified based on its sensitivity to compensate the blur occur at edges using fuzzy decision rules. The proposed approach results are superior to conventional methods in perceptual image quality as well as clarity and smoothness in edge region. Also, this approach provides a quite a stable performance over a wide variety of images with various noise densities.

Hussian *et al*.[12] proposed hybrid image restoration approach to detect and remove uniform impulse noise while preserving image details such as edges and texture information. The proposed approach uses two-stage robust mechanism which uses fuzzy filter with weighted median to construct the fuzzy membership function. The results show that the proposed technique performs significantly better in terms of peak signal to noise ratio, structural similarity index measure and subjective evaluation criteria.

Lei *et al*.[13] proposed adaptive Neuro-Fuzzy inference system for removing the impulse noise which is an optimization of median filtering, a wiener filtering and the Adaptive Neuro-Fuzzy Inference System (ANFIS). The proposed approach is tested with artificial images and obtained results shows that the proposed approach is efficiently restoring digital images corrupted by impulse noise without destroying the useful information on images.

Another researcher is proposed a novel approach for noise removal with two stages; first stage detects noise using adaptive Neuro-Fuzzy inference system and second stage find out changes in new pixels using fuzzy wavelet shrinkage[14]. The proposed approach results are better than the performance of fuzzy based approach and median filter based methods. Choubey *et al*.[15], proposed an approach for denoising ultrasound medical images. The proposed approach consists of the three stages includes pre-processing, training and testing. In first stage, medical images affected with adaptive white Gaussian noise (AWGN) are transformed using multi wavelet transformation. In second stage, the multi-wavelet coefficients of input are given to the adaptive Neuro-Fuzzy inference system. In third stage, the input image is examined using trained ANFIS for enhance the image quality by varying the threshold values to reproduce image.

Varghese *et al*.[16] proposed an approach using fuzzy functions for handling the uncertainties models while preserving the image textual features. The proposed approach of fuzzy functions provides more weights on the uncorrupted pixels that show much similarity with other uncorrupted pixels in the window while replacing the noise pixels. And also it adapts the different noisy levels as well as imagery conditions for reliability and robustness of suppressing noise while preserving images textual features. The results favoured the proposed filter in terms of subjective and objective metrics. Manel *et al*.[17] proposed a Neuro-Fuzzy system with on chip learning process for analysis of digital image processing task in edge detection.

Ellomi *et al*.[18] proposed a simple fuzzy model to detect and remove the salt and pepper noise, Gaussian mixed impulsive noise for both gray scale and color images. The proposed approach is designed based on fuzzy theory logic to reduce Gaussian and mixed impulsive noise from color images. Also, it uses fuzzy inference system to assign weight in weighted median filtering to remove noise. The proposed approach is tested with four different formats named as Tagged Image File Format (TIFF), (Bitmap) BMP, (Joint Photographic Experts Group) JPEG, and (Portable Network Graphic) PNG. The proposed approach performs better than existing works.

Taravat *et al*.[19], proposed non-adaptive approach combining both Weibull Multiplicative Model (WMM) and pulse-coupled neural networks for fully automatic darkspot detection on synthetic aperture radar images. At first, WMM is used to create a filter for speckle noise removal on each subimage which contains dark spots. Images are segmented using the Pulse-Coupled Neural Network (PCNN) method and then a filtering operation is performed for removal of false targets. The proposed

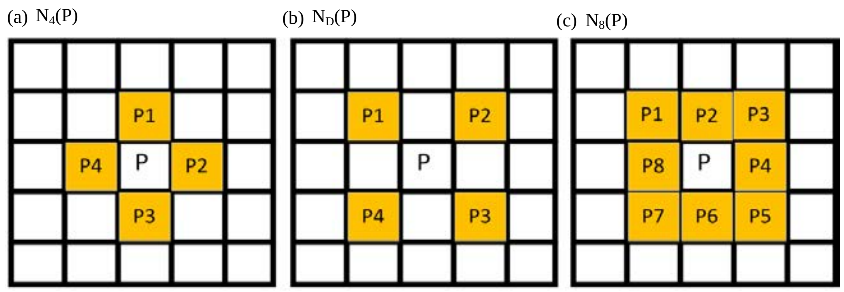


Fig. 1(a-c): Adjacency relationship

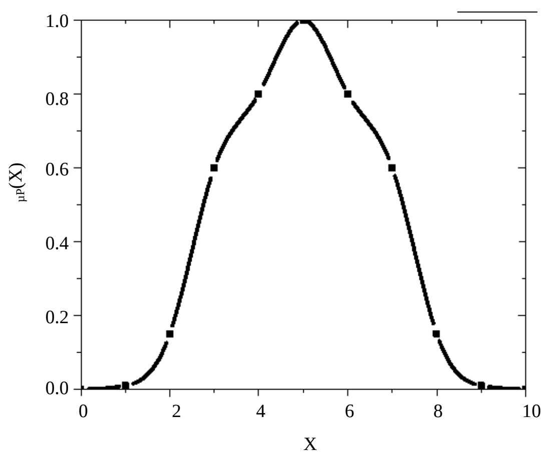


Fig. 2: Type-1 fuzzy set (Gaussian model)

approach is tested with 60 Envisat and ERS (Size 512×512) images which contain darkspots. The obtained results show the average accuracy is 93.66%.

Narnaware and Khedgaonkar[20], proposed an approach for image enhancement for improving visual appearance of images. The proposed approach uses artificial neural network and fuzzy logic for denoising and to enhance image quality. The obtained result shows the effectiveness of the proposed method by quantitative analysis and visual illustration. The performance evaluation is carried out with metrics such as (Peak Signal-to-Noise Ratio) PSNR, (Mean Squared Error) MSE, (Average Difference) AD and (Normalized Absolute Error) NAE.

As per the literature survey, it is understood that many techniques are existing to remove impulse noise from images using Neuro-Fuzzy approaches. It is observed that SAR images plays a major role in remote sensing applications, it is required to remove the noise from SAR images. Thus in this study, a novel approach to remove speckle noise is proposed.

**Background work:** In this study, the basics of pixels neighbouring relationship and Neuro-Fuzzy approaches are presented. In order to carry out image denoising operations, understanding of pixels neighboring relationship or topology is required.

**Adjacency relationship:** In general noise removal process using conventional approaches are carried out either in spatial domain or in frequency domain. In spatial domain, filtering process could be carried out either through convolution process or through correlation process of filter mask with original images. In general mask size is RXC where, R refers number of rows which is 2 N, -1, N = 1, 2, 3, ... and C refers number of columns which is 2 M -1, M = 1, 2, 3... During filtering process each pixel is replaced with a new pixel which is obtained after filtering process using its 4-adjacency $N_4(P)$, $N_D(P)$ and 8-adjacency $N_8(P)$ relationship. The adjacency relationship of any pixel is shown in Fig. 1 a-c, respectively.

**Neuro-fuzzy system:** In this study, basics of neural networks, type1 and type 2 Neuro-Fuzzy sets are presented. In the subsequent section neural networks is discussed briefly (Fig. 2).

**Neural networks:** In a simple neural network system $X_i = \{x_1, x_2, x_3, ..., x_n\}$ represents input signal and $W_i = \{w1, w_2, w_3, ..., w_n\}$ represents weights corresponding to inputs. The input signal is multiplied with appropriate weights as shown in Eq. 1 to calculate net output using Eq. 2:

$$P_i = \{P_1, P_2, P_3, ..., P_n\} = X_i\ W_i \text{ where} = \{1, 2, 3, ..., n\} \quad (1)$$

$$\text{net} = \sum_{i=1}^{n} P_i = \sum_{i=1}^{n} X_i W_i \quad (2)$$

The calculated net output is given as input to non-linear transfer function f to obtain final output Y using Eq. 3:

$$Y = f(\text{net}) = f\left\{\sum_{i=1}^{n} X_i W_i\right\} \quad (3)$$

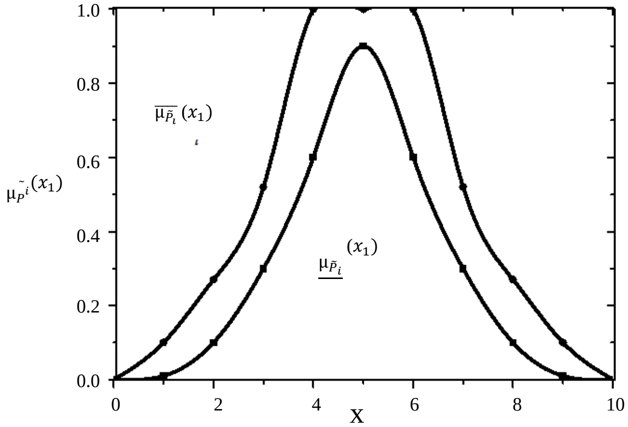


Fig. 3: Type-2 fuzzy set (Gaussian model)

Here, the transfer function f could be any non-linear transfer function.

**Type-1 Neuro-Fuzzy Set (T1NF):** The type-1 fuzzy set $P_i$ on given universal set $X_i = \{x_1, x_2, x_3, ..., x_n\}$ is represented in Eq. 4:

$$P_i = \left\{\left(x_1, \mu_{P_i}(x_1)\right) \mid \forall\, x_1 \in X_i\right\} \tag{4}$$

Where:
$\mu_{pi}$ = The membership function
$P_i$ = Closed interval of set
$X_i$ = Between zero and one as given in Eq. 5

$$\mu P_i : X_i \rightarrow [0,1] \tag{5}$$

The graphical representation of type-1 Neuro-Fuzzy set is shown in Fig. 2.

**Type-2 Neuro-Fuzzy Set (T2NF):** The type-2 fuzzy set $\tilde{P}_i$ Pon given universal set $\{x_1, x_2, x_3, ..., x_n\}$ where $x_1<x_2<x_3<....<$ can be represented as shown in Eq. 6:

$$\tilde{P}_i = \left\{\left(x_1, \mu_{\tilde{P}_i}(x_1)\right) \mid \forall x_1 \in X_i\right\} \tag{6}$$

Where $\mu\tilde{P}_i$ represents the secondary membership function in which each member have fuzzy values that refers from type-1 fuzzy as shown using Eq. 7 (Fig. 3).

$$\mu_{\tilde{P}_i} = \int_{u \in I_{x_1}} \frac{\mu_{\tilde{P}_i}(u)}{u} \tag{7}$$

Here, $I_{xi} \subseteq [0, 1]$ $0 \leq I_{xi} \leq 1$. In this study, the type-2 fuzzy set $\tilde{P}_i$ defined on a universal set $X_i$ and it has secondary function as given in Eq. 8 is used from[21, 22]:

$$\mu_{\tilde{P}_i}(x_1) = \text{gauss}(u; \text{guass}(x_1; m^p, \sigma^p), \sigma^s) \tag{8}$$

Here, $x_1 \in X_i$, $\mu \in [0, 1]$ and guass $(x^1; m^p, \sigma^p)$ is the Gaussian membership function with mean (m) and standard deviation ($\sigma$) defined as follows:

$$\text{Gauss}(x_1; m^p, \sigma^p) = \exp\left[-\left(\frac{x_1 - m}{\sigma}\right)^2\right] \tag{9}$$

The graphical representation of type-2 Neuro-Fuzzy set is shown in Fig. 3. The inner Gaussian $(x_1; m^p, \sigma^p)$ is primary membership function of $\tilde{P}_i$ which is type-1 interval fuzzy set with $u \in [0, 1]$:

## MATERIALS AND METHODS

**Proposed methodology:** In this study, the proposed system for speckle noise reduction is presented in detail. The proposed system uses both artificial neural network and fuzzy logic concepts to develop filtering model. In particular, type-2 Neuro–Fuzzy approach is exploited in this proposal as it is well suited for speckle noise which is uncertain in nature. The basic structure used in this proposal is shown in Fig. 4.

The input to the system is image affected with speckle image. The fuzzy inference system fuzzyfies inputs and applies fuzzy rules using type-2 Gaussian membership function to generate final output. The centroid defuzzification method is used to convert fuzzy input into output pixel which is free from noise. In the subsequent section, the basics of adjacency and topology concepts used in this proposal are discussed in detail.

**Adjacency and topology:** In this proposal, a sliding window of size 3×3 is used to perform filtering operation. The coordinate position of a sliding window of size 3×3 is shown in Fig. 5. The window, slide over an input image and encompasses 3×3 pixels at any given point. At a given position three pixels including centre pixel are selected for filtering operations. There three adjacency adopted to remove speckle noise, they are 4-adjacency $N_4(P)$ with two topology, 4-adajacency $N_D(4)$ with two topology and 8-adjacency $N_8(P)$ with four topology. The four basic topology adopted in this work are shown in Fig. 6. In the subsequent section fuzzy inference system is discussed in detail.

**Fuzzy Inference System (FIS):** In this proposal, Sugeno-type fuzzy inference system is used to remove noise from images. In this system one topology is used at a time to filter an image. A block of pixels associated with selected topology is given as inputs to FIS which fuzzifies inputs and apply fuzzy rules. The selection of adjacency decides the topology to be used and corresponding blocks to be

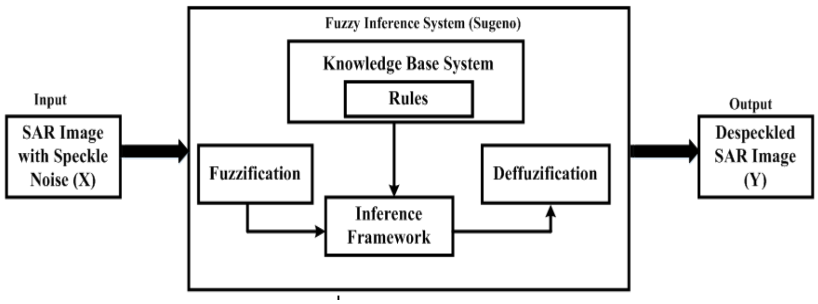


Fig. 4: Neuro-fuzzy based filtering system

| | | |
|---|---|---|
| X[n-1,p-1] | X[n-1,p] | X[n-1,p+1] |
| X[n,p-1] | X[n,p] | X[n, p+1] |
| X[n+1,p-1] | X[n+1,p] | X[n+1,p+1] |

Fig. 5: Sliding window of size 3×3 and its coordinate position

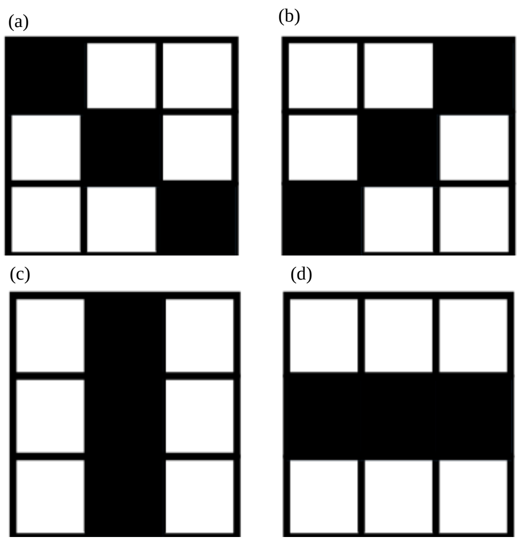


Fig. 6: Four different topology (a) Left decision (b) Left diagonal ( c) Right diagonal and Vertical and horizontal

selected for filtering operations. Each block consists of three pixels and are denoted by $\{x_1^r, x_2^r, x_3^r\}$ and $Y_r$ denoted by output. Here, r represents order of rule in FIS. The fuzzy rules used in FIS are given:

If $\left(x_1^r \in \mu^r_{\tilde{P}_{11}}\right)$ and $\left(x_2^r \in \mu^r_{\tilde{P}_{12}}\right)$ and $\left(x_3^r \in \mu^r_{\tilde{P}_{13}}\right)$ then $O_1^r = \alpha_{11}^r x_1^r + \alpha_{12}^r x_2^r + \alpha_{13}^r x_3^r + \alpha_{14}^r$

If $\left(x_1^r \in \mu^r_{\tilde{P}_{21}}\right)$ and $\left(x_2^r \in \mu^r_{\tilde{P}_{22}}\right)$ and $\left(x_3^r \in \mu^r_{\tilde{P}_{23}}\right)$ then $O_2^r = \alpha_{21}^r x_1^r + \alpha_{22}^r x_2^r + \alpha_{23}^r x_3^r + \alpha_{24}^r$

If $\left(x_1^r \in \mu^r_{\tilde{P}_{31}}\right)$ and $\left(x_2^r \in \mu^r_{\tilde{P}_{32}}\right)$ and $\left(x_3^r \in \mu^r_{\tilde{P}_{33}}\right)$ then $O_3^r = \alpha_{31}^r x_1^r + \alpha_{32}^r x_2^r + \alpha_{33}^r x_3^r + \alpha_{34}^r$

Suppose the i[th] membership function of fuzzy rules in FIS is representing as follows:

If $\left(x_1^r \in \mu^r_{\tilde{P}_{i1}}\right)$ and $\left(x_2^r \in \mu^r_{\tilde{P}_{i2}}\right)$ and $\left(x_3^r \in \mu^r_{\tilde{P}_{i3}}\right)$ then $O_i^r = \alpha_{i1}^r x_1^r + \alpha_{i2}^r x_2^r + \alpha_{i3}^r x_3^r + \alpha_{i4}^r$

Similarly, N[th] the membership function of fuzzy rules in FIS is representing as:

IF $\left(x_1^r \in \mu^r_{\tilde{P}_{N1}}\right)$ and $\left(x_2^r \in \mu^r_{\tilde{P}_{N2}}\right)$ and $\left(x_3^r \in \mu^r_{\tilde{P}_{N3}}\right)$ then $O_N^r = \alpha_{N1}^r x_1^r + \alpha_{N2}^r x_2^r + \alpha_{N3}^r x_3^r + \alpha_{N4}^r$

Here, N represents the number of fuzzy rules in FIS, $\mu^r_{\tilde{P}_{ij}}$ represents the i[th] position membership of i[th] input of NF system and $O^r_i$ denotes the output of i[th] rule in FIS. However, the Gaussian Type-2 interval fuzzy set membership function using intervals with uncertain mean formula is specified as (Fig. 7 and 8):

$$\mu^r_{\tilde{P}_{ij}}(u) = \exp\left[\frac{-1}{2}\left(\frac{u - em^r_{ij}}{\sigma^r_{ij}}\right)^2\right] \quad (10)$$

But, $em^r_{ij} \in \left[\underline{em^r_{ij}}, \overline{em^r_{ij}}\right]$, I = 1, 2, 3, ..., N; j = 1, 2, 3,..., N

Where, $em^r_{ij}$ and $\sigma^r_{ij}$ the and are the mean and standard deviation of the type-2 interval Gaussian membership

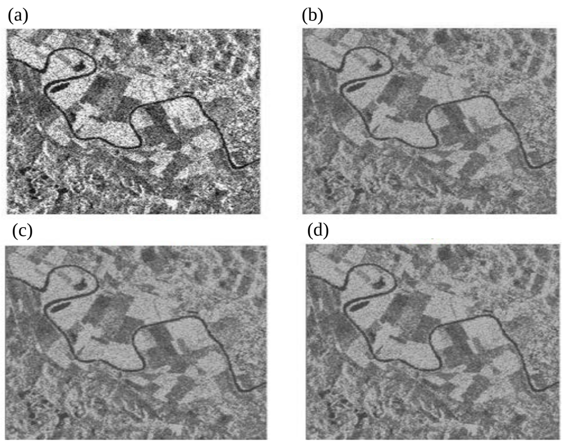


Fig. 7: Orignal and denoised SAR image (a) Orignl image (b) $N_4$p ( c) $N_D$ (8) and d $N_8$ (P)

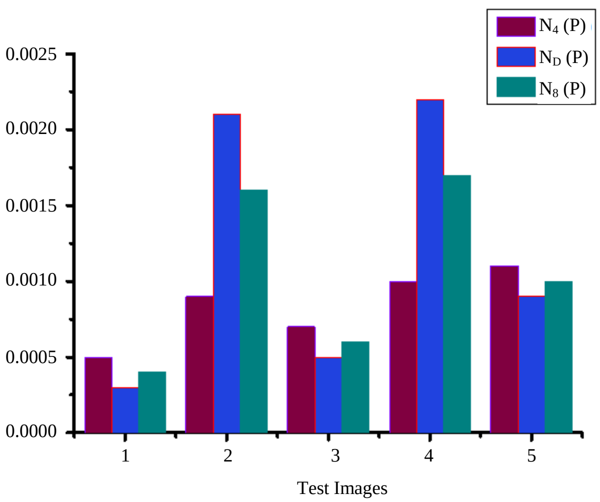


Fig. 8: The obtained result for MSE

function of $\mu^r_{\tilde{P}_{ij}}$ intervals $\left[\underline{em}^r_{ij}, \overline{em}^r_{ij}\right]$ is lower and upper bounds of uncertainty mean. Also, the sample type-2 interval Gaussian membership functions with associated uncertainty is defined as:

$$\underline{\mu}^r_{\tilde{P}_{ij}}(u) = \begin{cases} \exp\left[\frac{-1}{2}\left(\frac{u - \underline{em}^r_{ij}}{\sigma^r_{ij}}\right)^2\right] & u > \frac{\underline{em}^r_{ij} + \overline{em}^r_{ij}}{2} \\ \exp\left[\frac{-1}{2}\left(\frac{u - \overline{em}^r_{ij}}{\sigma^r_{ij}}\right)^2\right] & u < \frac{\underline{em}^r_{ij} + \overline{em}^r_{ij}}{2} \end{cases} \quad (11)$$

And

$$\overline{\mu}^r_{\tilde{P}_{ij}}(u) = \begin{cases} \exp\left[\frac{-1}{2}\left(\frac{u - \underline{em}^r_{ij}}{\sigma^r_{ij}}\right)^2\right] & u > \frac{\underline{em}^r_{ij} + \overline{em}^r_{ij}}{2} \\ \exp\left[\frac{-1}{2}\left(\frac{u - \overline{em}^r_{ij}}{\sigma^r_{ij}}\right)^2\right] & u < \frac{\underline{em}^r_{ij} + \overline{em}^r_{ij}}{2} \end{cases} \quad (12)$$

Here, $\underline{em}^r_{ij}$ and $\overline{em}^r_{ij}$ are the lower and upper membership functions of the type-2 interval fuzzy system $em^r_{ij}$, respectively. The final output of $i^{th}$ FIS is weighted average of individual rule output and is calculated by:

$$Y_r = \frac{\sum_{i=1}^{N} W^r_i O^r_i}{\sum_{i=1}^{N} W^r_i} \quad (13)$$

Here, $W^r_i$ is weight factor of $i^{th}$ rule which is calculated as given:

$$W^r_i = \mu^r_{\tilde{P}_{i1}}\left(x^r_1\right) * \mu^r_{\tilde{P}_{i2}}\left(x^r_2\right) * \mu^r_{\tilde{P}_{i3}}\left(x^r_3\right) \quad (14)$$

The weight is $W^r_i = \left[\underline{w}^r_i, \overline{w}^r_i\right]$ the lower and upper boundaries are determination by using the respective membership functions defined as follows:

$$\underline{w}^r_i = \underline{\mu}^r_{\tilde{P}_{i1}}\left(x^r_1\right) * \underline{\mu}^r_{\tilde{P}_{i2}}\left(x^r_2\right) * \underline{\mu}^r_{\tilde{P}_{i3}}\left(x^r_3\right) \quad (15)$$

$$\overline{w}^r_i = \overline{\mu}^r_{\tilde{P}_{i1}}\left(x^r_1\right) * \overline{\mu}^r_{\tilde{P}_{i2}}\left(x^r_2\right) * \overline{\mu}^r_{\tilde{P}_{i3}}\left(x^r_3\right) \quad (16)$$

Where, $\underline{w}^r_i$ and $\overline{w}^r_i$ are denotes the lower and upper boundaries of the interval weighting factor $W^r_i$ of the $i^{th}$ rule, respectively. After applying the weighted factors output $Y_r$ is the $r^{th}$ NF filter can be computed based on the average weight factors is using the individual rule outputs from Eq. (13). The output $Y_r$ is computing in type-1 interval fuzzy set; i.e., $Y_r = \left[\underline{y}_r, \overline{y}_r\right]$. It is calculated from eq. (14) of weights $W^r_i$ are type-1 interval sets and $O^r_i$ is single scalar value output, is determined by the lower and upper boundaries of $Y_r$ using with iterative processes is refered Starczewski[22].

**Defuzzifier:** Defuzzifier converts fuzzy values into single scalar value. In this proposal centroid defuzzification approach is used to get scalar output value as given in Eq. 17:

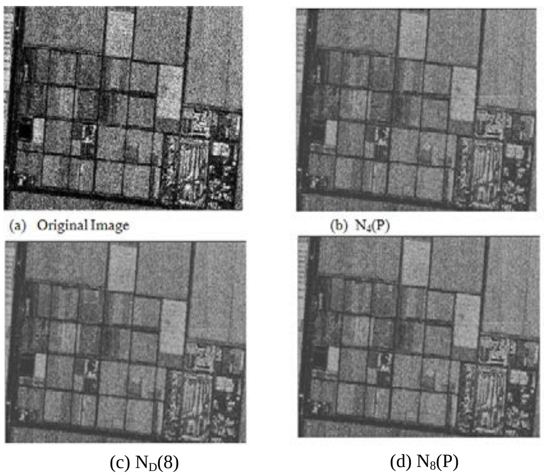


Fig. 9: Orignal and denoised SAR image

$$D_{Y_r} = \frac{y_r + \overline{y_r}}{2} \tag{17}$$

In Eq. 17 the middle value of is calculated by taking centroid of it. Similarly using (Eq. 18), the value of final output of each filter is obtained:

$$D_{OP} = \frac{1}{K}\sum_{r=1}^{K} D_{Y_r} \tag{18}$$

The filtering process using proposed approach is presented as algorithms in the subsequent section.

Algorithm
Input Image: X(a, b)
Output Image: Y(a, b)
Sliding window of required size is selected
Adjacency relation with centre pixel is selected to decide topologies to be used
The filtering operation is started from the upper-left corner of the image
Window slide over an image from left to right and top to bottom
Blocks corresponding to each topology is given to FIS which produce filtered output
Sliding window centre pixel is replaced with a new filtered pixel
Goto step 4 till it completes filtering operation with an entire image

## RESULTS AND DISCUSSION

**Performance analysis:** In this study, the performance analysis of the proposed work is carried out with test images of various sizes and it is simulated. Speckle noise removal is carried out with the sliding window of size 3×3. In order to reduce complexity of the proposed work the window size is kept at 3×3 shown in Fig. 1. The neighbouring relationship of any pixel P is called adjacency. The filtering operation could be carried out by

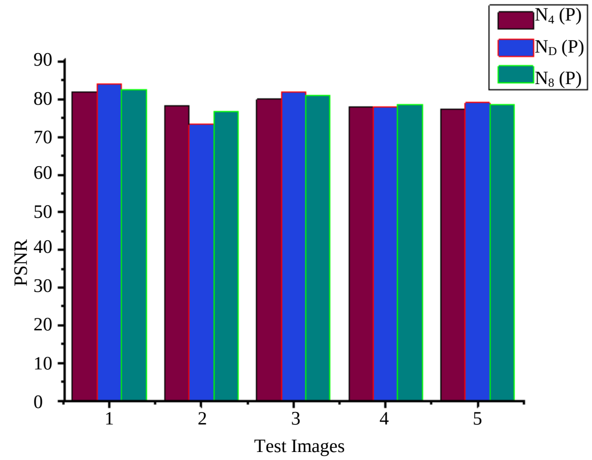


Fig. 10: Obtained result for PSNR

Table 1: Obtained Mean Square Error (MSE)

| | Mean square error<br>Pixel adjacency relation | | |
|---|---|---|---|
| Test images | $N_4$(P) | $N_D$(P) | $N_8$(P) |
| 1-512×512 | 0.0005 | 0.0003 | 0.0004 |
| 2-512×512 | 0.0009 | 0.0021 | 0.0016 |
| 3-256×256 | 0.0007 | 0.0005 | 0.0006 |
| 4-256×256 | 0.0010 | 0.0022 | 0.0017 |
| 5-256×256 | 0.0011 | 0.0009 | 0.0010 |

considering horizontal and vertical neighbour of a centre pixel p in sliding window as shown in Fig. 1a, four diagonal neighbour of a centre pixel P as shown in Fig. 1 b and all neighbours of centre pixel as shown in Fig. 1 c. In order to evaluate the performance of the proposed work five test images of various sizes used. The output image quality is measured using subjective and objective metrics. The subjective measure is very good for obtained results, similarly objective measure such as Mean Square Error (MSE), Peak Signal to Noise Ratio (PSNR) is calculated using Eq. 19 and 20:

$$MSE = \frac{1}{MN}\sum_{r=1}^{N}\sum_{c=1}^{M}\left(Y(r,c) - X(r,c)\right) \tag{19}$$

$$PSNR = 10\log_{10}\left(\frac{255^2}{MSE}\right) \tag{20}$$

In Fig. 7, (a) represents original SAR image with speckle noise, (b) represents denoised SAR image with $N_4$(P) adjacency, (c) represents denoised SAR image with $N_D$(P) adjacency and (d) represents denoised SAR image with $N_8$(P) adjacency. The obtained results for $N_4$(P), $N_D$(P), and $N_8$(P) is shown in Table 1 and its graphical representation is shown in Fig. 8. Similarly Fig. 9 shows

Table 2: Obtained peak signal to noise ratio

| | Peak signal to nMarch 31, 2021oise ratio in dB Pixel adjacency relation | | |
|---|---|---|---|
| Test images | $N_4(P)$ | $N_D(P)$ | $N_8(P)$ |
| 1-512×512 | 81.9212 | 83.9591 | 82.5245 |
| 2-512×512 | 78.3152 | 73.2432 | 76.8321 |
| 3-256×256 | 79.9870 | 81.7734 | 81.0752 |
| 4-256×256 | 78.0568 | 77.9166 | 78.6569 |
| 5- 256×256 | 77.3090 | 79.0130 | 78.6368 |

denoised SAR images with various adjacency relationships. The obtained results are shown in Table 2 and Fig. 10.

## CONCLUSION

In this study, a novel Neuro-Fuzzy based approach is proposed for removing speckle noise from SAR images. In particularly, type-2 Neuro-Fuzzy approach is used to remove speckle noise as it is well suited for high uncertainty of noise occurrence. This proposed system is tested with images of sizes 256×256 and 512×512. The quality of output images are measured using objective and subjective metrics. The obtained results show the efficiency of the proposed method.

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