FUZZY NEURAL NETWORK OPTIMIZATIONAPPROXIMATE MULTIPLIERUSING NONLINEAR ANISOTROPIC IMAGE DENOISING

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ABSTRACT

Multiplier is playing asignificant role in a wide range of applications including like embedded systems, VLSI, and digital signal processing. Computation is significant in image processing. In image processing, various problems occur in neural networks.Computational is to solve the problem.The processing of computation is power consumption, design complexity, andreduces the error.The fuzzy neural network optimization approximates multiplier using the nonlinear anisotropic diffusion image denoisingmethod.The noise image from the input images is removed using nonlinear anisotropic diffusion image denoising.The fuzzy neural network optimization of an approximate multiplieris used to minimize the design complexity and increase the speed.The FNNOAM-NLADID method implements the neural network system to remove the noisy image and develop the design on a multiplier basis. This method is utilized to design the ideal components: adder, tree, and compressor. A neural network system is an essential part of our body. The FNNAOM-NLADID method performs power consumption, peak signal-to-noise ratio, error and noise; these factors are considered in the design.Digital signal processing in real time to computational building block, arithmetic and logic unit, and accumulator.This method, FNNOAM-NLADID based on the decreased design complexity and power consumption to achieve the technique.Neural networks simplify the mathematics of complex input and output and reduce the multiplicative noise.

Keywords: **Fuzzy neural network, denoising, noise, multiplier, power consumption**

DOINumber:10.14704/nq.2022.20.8.NQ22270 **NeuroQuantology2022;20(8):2477-2491**

1. INTRODUCTION

A fuzzy neural network system to simplify the complex input and output. The multiplier is used in a wide range of applications such as digital signal processing, VLSI, etc. In the digital world, accuracy is most important, so to produce the accuracy using computation process because accuracy is not in many approaches. The accuracy of image processing removes the error, and good performance and noise are reduced. A fuzzy neural network also reduces the multiplicative noise.

Multiplicative noise in ultrasound images in [1]proposes inappropriately, the multiplicative noise that exists in these images makes correct diagnosis extremely complex and difficult for specialists. As a result, multiplication noise reduction is a critical challenge in the development of an effective diagnostic system. Fuzzy logic is used to minimize multiplicative noise in this article. Different current de-noising algorithms are compared to the proposed technique, including feature analysis such as segmentation, selecting a region of interest, and seed point selection.

Fuzzy neural network system application in handwritten[2] For processing the physical data of the pictures accessible for the handwritten digits, fuzzy filters are used with neural nets. The use of fuzzy filters minimizes the amount of noise and redundancy in the data, which improves the model's performance.The fuzzy filters with higher dimensionality improve the model recognition rate. One-dimensional and two-dimensional fuzzy filters are discussed, and their performance is evaluated.

Hybrid neuro-fuzzy models [3] to produce a good performance scheme are based on a termed Fuzzy Convolutional Neural Network. There is a problem with noise while detecting and identifying words in scene photos. Because of the low light intensity, this noise may exist. Because the suggested model combines Neural Networks and Fuzzy Logic, it will be able to learn and handle uncertainties in the picture that has been damaged by noise.

Convolutional neural networks (CNNs)[4] are deep neural networks. The different processes are involved classification of, segmentation and denoising of images. To improve the image quality using many image denoising techniques. The comparison of non-CNN and CNN methods such as three-dimensional filtering and block matching.

In [5] image filtering technique reduces noise from image analysis tools.Denoisingis used in some applications, such as segmentation, to smooth uniform regions while keeping outlines. Many applications, such as image-guided, surgical treatments, video analysis, and visual serving require real-time denoising.

1.1 RESEARCH WORK CONTRIBUTIONS:

- The FNNOAM-NLADID method reduces the noise from the input images.
- This method for neural networks simplifies the complex mathematical input and output.
- This research work also reduces the power consumption and Noise handling of a fuzzy neural network system.
- FNNOAM-NLADID method reduces the multiplicative noise

2. LITERATURE SURVEY

In [6], Chandrajit Pal presented the removal of noise to increase signal processing performance using anisotropic diffusion filtering combining FPGA.The suggested method removes the high-frequency components for images without the blurring of images helping anisotropic filtering the performance of image reconstruction quality by convolution process. To reduces the power consumption and usage of the resource. However, the error was not reduced.

In [7], Sandhi Naresh, proposes the high-speedapproximated multiplier circuit to decrease the path delay and power consumption. The TDM method carries the tree and facilitates the implementation of FPGA. The design complexity occurred.

In [8] Sasipriya P, use the efficient approximate multipliers and adders used to reduce the error and increase the performance using the 8x8 Dadda multiplier to evaluate the delay, space, and error. Most of the signal processing algorithms is a multiplier to extend the power. They carry the tree and computation result. To generate total product and carry and reduce the tree.But power consumption is not reduced.

In [9] Pranose j edavoor, the design of multiplier helps of 4:2 compressor architectureused to reduce the delay, areaand power. Additional that CMOS technology produces accurate output. The suggested compressor uses two multipliers, 8x8 and 16x16 are high-speed architecture implemented for smoothing images and reducing the power dissipation.

In [10] M. GiridharReddy, errortolerance is used to design the multiplier in digital signal processing to reduce area and power consumption. To design the low power techniques, approximate multiplier combing CMOS and ECRL logic.ECRL is the most suitable for power dissipation of critical parameters.

In [11] Minho Ha.Design the 4-2 compressors based onan approximate multiplier. A multiplier is a fast computation solution for electronic circuits. The planned 4-2 compressor is used for an error recovery application. The multiplier to produce accurate results of error recovery. However, design complexity occurs.

In [12] A.V.S.S Varma, the Field programmable gate arrayis implemented for accurate design and high performance. Multiplier design involves the four steps barrel shift register, pre-processing, post-processing, and parallel adder. We simulated the design using Xilinx software. The FPGA is based on a multiplier utilized for an application-specific integrated circuit.

In [13], Mei Gao suggested that a system in image processing to remove noise is essential, particularly speckle noise. The anisotropic diffusion model on image statistics such as a gradient of image, noise standard and grey levels. The proposed experiments improve the model criteria on kurtosis and correlation. Additionally, that is used to take colour images using RGBand represent partial differential equations. The result of this method is to remove the speckle noise, colour image and image denoising.

In [14] RezaZendegani, the suggested method of an approximate multiplier in digital signal processing performs both signed and unsigned applications.SpeciallyRoBA multiplier is used in this work to produce the output in smoothening and image sharpening.This approach worked on the hardware and simulation process involved. The result is image processing of sharpening and smoothening, but performance is reduced.

In [15]honglanjiang, the suggested method booth multiplier is used for high performance on encoding the products. Booth multiplier also reduces the power consumption and accuracy of the hardware setup. 16x16 bit approximate radix booth multiplier. The overall performance improved.However, hardware implementation is very difficult.

3. METHODOLOGY

The fuzzy neural network optimization is based on a nonlinear anisotropic diffusion image denoising method to simplify the complex input and output.The multiplieris processed in the digital signal processor, embedded system, and subsystem with many applications. Most Electronic devices consist of power consumption needed and are processedovera long-time duration. The fuzzy neural networks help reduce the overall losses and improve accuracy. The optimizer is an algorithm andfunction to modify attributes such as weights and learning dates. The image denoising of this system removes the noisy artefacts from the images. The proposed method is discussed in two parts that are combined with working to execute a better performance. Fuzzy neural network optimization and nonlinear anisotropic diffusion imagedenoisingare discussed in following sections 3.1 and 3.2.approximate multiplier represents the section 3.3,multiplicative noise represents section 3.4.

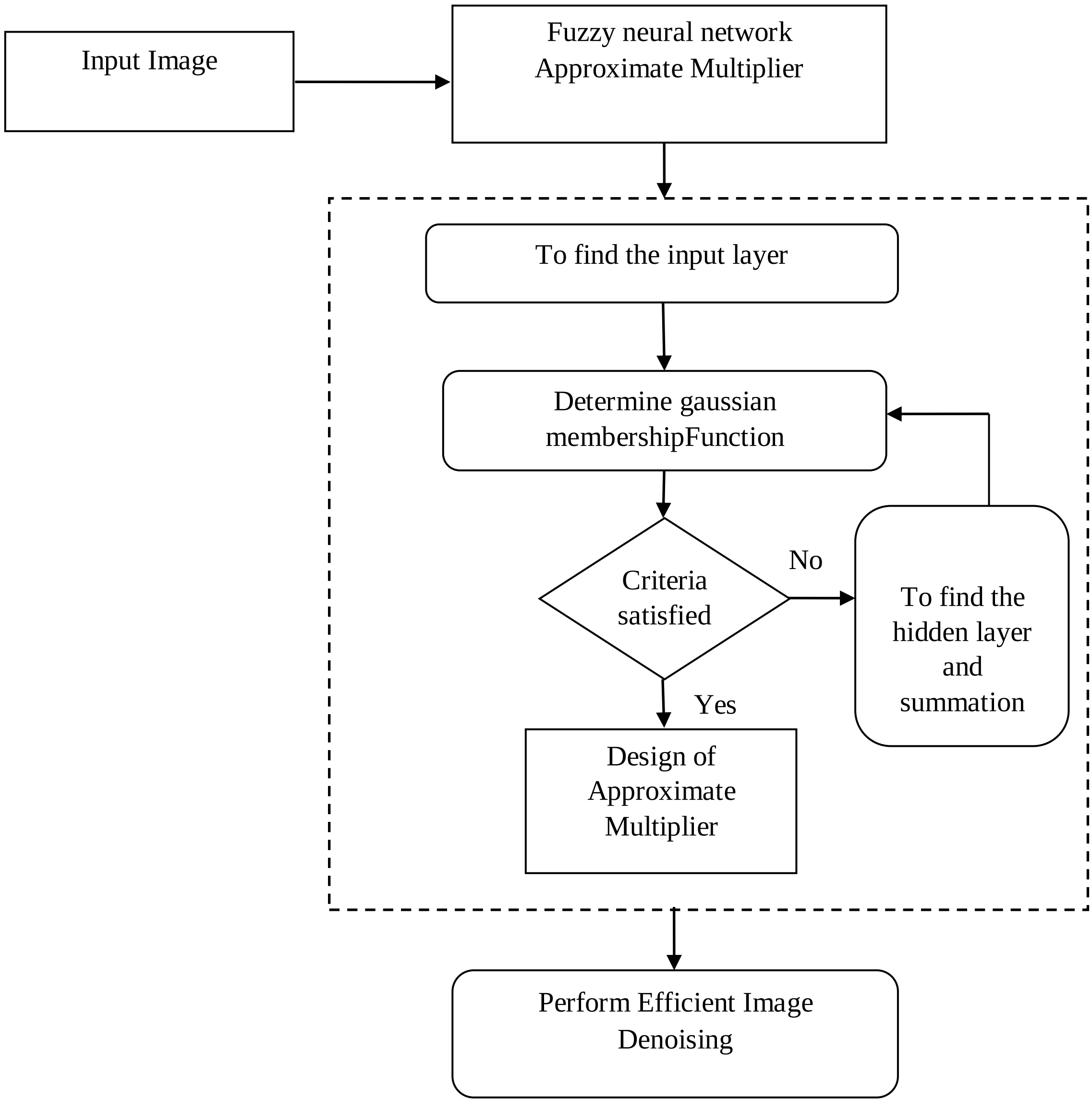

Figure 1Overflow Diagram of Fuzzy Neural Network Optimization Approximate Multiplier Based On Nonlinear Anisotropic Diffusion Image Denoising

3.1 FUZZY NEURAL NETWORK OPTIMIZATION

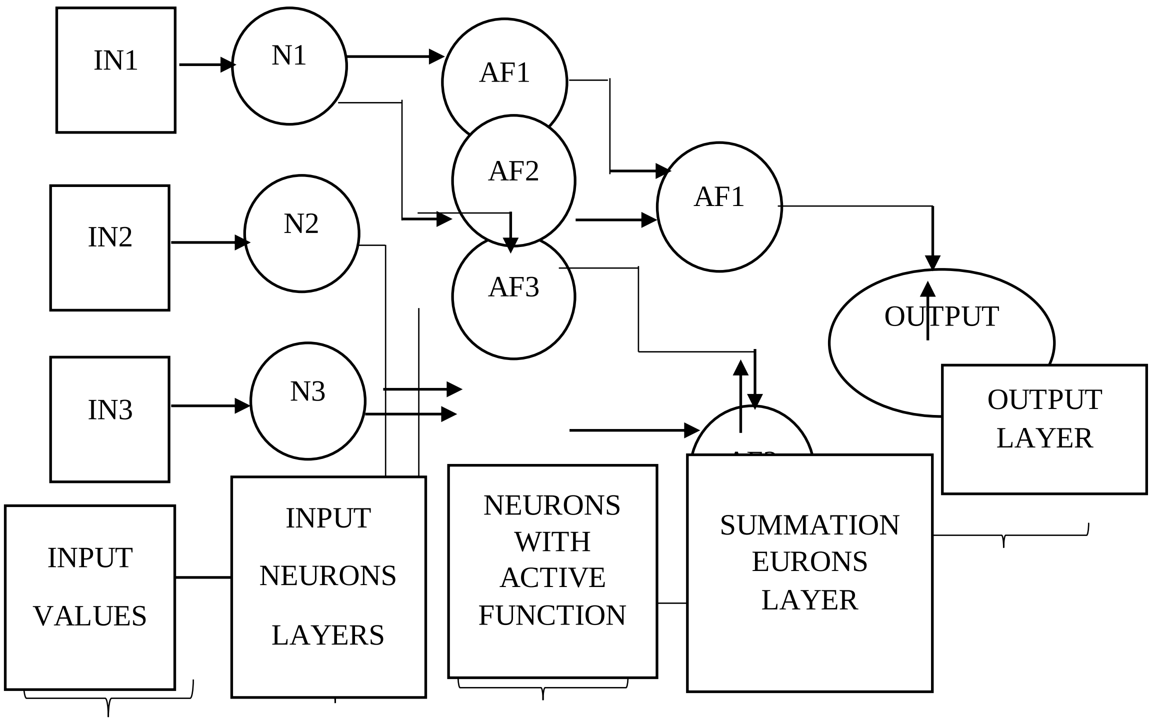

Figure 2Fuzzy Neural Network System

A neural network system consists of a series of an algorithm to determine and identify the problems.A neural network is a mathematical model to simulate and solve the complicated data patterns and difficulties of forecasting. Neural network algorithms are created by repeating and operating the brain's procedures as an initial point. Because it is capable of simulating the human brain's functions and activity. A neural network is an algorithm that consists of a network of neurons, each of which is a mathematical function that gathers and classifies input from a certain model. The input neuron layer of a neural network is made up of user inputs. The activation function layer determines the output. Depending on the context, it may have many activation function layers. The summation layer combines the output of the activation function layer and displays it in the output layer section.

Algorithm 1:

//Verification AND gate using neural network
Data: Input values I_1 and I_2 and weight nodes (W_1 and W_2)
Result : 0 or 1
Incoming signal =I_1*W_1 and I_2*W_2
If incoming signal >T, then
  Generate output: 1
Else:
  Generate output :0
  Return
End

Fuzzy neural networks represent the normal input and output variables, and the hidden layer denotes the fuzzy logic rules. The fuzzy value indicates the weighted values. The weighted values directly encode the fuzzy rules in the neural network.Membership function in fuzzy defined the weight of fuzzy rule and neuron is connected to membership function. Membership functions can take any form and communicate previous language standards. The variance of a Gaussian membership function may be the same as that of a receptive field unit:

$$y = \mu(x) = \mathrm{e}^{-((x-c)^2/2\sigma^2)}$$

Here,

c- centre of the membership function

σ- width of membership function

The neural network adjusts the fuzzy symbolic representation by using gradient descent to control the parameter of the membership function that dictates its form (width and centre location).

The function of FNN system defined as,

$$y_i = f(W, g, x) = \sum_{j=1}^{n} w_{ij} g\left(\sum_{k=1}^{m} w_{jk} x_k + w_{j0}\right) + w_{i0}$$

The radial basis function network performs mapping in network mapping among inputs and outputs using n local receptive fields:

$$R_i(x) = R_i\left(|x - c_i|/\sigma_i^2\right)$$

The maximum response of respective field function concerning width by gaussian σ: 2482

$$R_i(x) = \mathrm{e}^{-|x-c_i|2/\sigma_i^2}$$

The output is the sum of each receptive field function's weighted input values:

$$y = f(x) = \sum_{i=1}^{n} w_i R_i(x)$$

This is identical to the fuzzy AND-OR operator. The following people provide weight updates:

$$w_i(t) = w_i(t-1) + \eta_i\left(x(t) - w_i(t-1)\right)$$

To minimize the error among the intended and output network.The width and centre of these parameters affect the membership function and diagnose the problem using Kohonen self-organizing map algorithm. The function centre is defined by the following factors: This is identical to the fuzzy AND-OR operator. The updating weight is given by:

$$|x - W_i| = min|x - W_j|$$

Wj = winner’s weight vector

Weight update is given by

$$W_i(t+1) = W_i(t) + \eta_i(t) h_{ij}(t)\left(x(t) - W_i(t)\right)$$

Where,

$h_{ij}(t) = exp\left(-\frac{d_{ij}^2}{\sigma^2(t)}\right)$ = neighborhood function,

dij(t)= $|W_i - W_j|$ = distance between nodes i and j,

σ(t) = width,

ηi(t) = learning parameter.

The N-nearest neighbours algorithm might be used to find the breadth of the membership function by minimizing the objective function:

$$E = \frac{1}{2} \sum_{i=1}^{n} \left(\left(\frac{d_{ij}}{\sigma_i}\right)^2 - r\right)^2$$

where r = overlap parameter.

The correlation strength of input and output variables based on the firing strength of the rule is defined as the T-norm or minimum (multiplication) operator of the membership function:

$$w_i = \mu_{\mathrm{A}}(x_1)\mu_{\mathrm{B}}(x_2) = min\left(\mu_{\mathrm{A}}(x_1), \mu_{\mathrm{B}}(x_2)\right)$$

The overall output is the weighted sum of each rule's output:

$$f(x) = \sum_{i=1}^{n} w_i f_i$$

where n = No.of fuzzy rules.

The number of receptive field units equals the number of fuzzy rules. The membership function may be written as follows:

$$\mu_{\mathrm{A}}(x_1) = k_1 exp\left(-\frac{(x_1 - c_{\mathrm{A}})^2}{\sigma_1^2}\right)\text{and}\mu_{\mathrm{B}}(x_2) = k_2 exp\left(-\frac{(x_2 - c_{\mathrm{B}})^2}{\sigma_1^2}\right)$$

The firing strength (weight)is defined as based on rule i

$$w_i(x_1, x_2) = \mu_{\mathrm{A}}(x_1)\mu_{\mathrm{B}}(x_2) = exp\left(-\frac{|x - c_i|2}{\sigma_1^2}\right) = R_i(x)$$

3.2 PROCESS OF NON-LINEAR ANISOTROPIC DIFFUSION IMAGE DENOISING

The non-Linear anisotropic diffusion imagedenoising technique improves image quality by removing noise from input images. Consider the dataset 'd,' which has animage count of 'd=i_1, i_2... i_n,'.

Here,

n- Total No. of images.

In the FNNOAM-NLADID approach contains partial differential equation using diffusion in anisotropic as defined by, 2483

$$\frac{\partial i}{\partial t} = div$$

$$\frac{\partial i}{\partial t} = \nabla c . \nabla i + c(u, v, t)\Delta i$$

From above equations,
'Δ' -Laplacian
'∇' -Gradient.
'$div()$' -Divergence operator
'$c(u, v, t)$' - Diffusion coefficient
Filter in non-linear equation is defined as,

$$i^f(x) = \frac{1}{N}\sum_{x_j} i(x_j)\, r_k(|\|i(x_j) - i(x)\||)$$

Here,
'i^f' -Filtered image
'j' -Original input image
'x' -Coordinates of current pixel
r_k' -Range kernel
'N' -Normalization terms
Imagequalitydefined by,

$$w = \sum_{x_j} r_k(\|i(x_j) - i(x)\|) s_k(\|x_j - x\|)$$

From above equation

's_k'represents the spatial kernel in coordinates.

Image of Non-Linear Anisotropic Diffusion The weight 'w' of the Denoising Filter is determined by closeness and intensity fluctuation. Neighbouring pixels and one of the pixels at '(y, z)' in the picture de-noise a pixel at '(u, v)' in the image. The following is how the weights are calculated:

$$w(u,v,y,z) = exp(-\frac{(u-y)^2 + (v-z)^2}{2\alpha^2} - \frac{\|i(u,v) - i(y,z)\|^2}{2\beta^2}$$

Here
α andβ - smoothing parameters.
*i(u, v)*and i (y, z) – the intensity of pixels for (u, v) and (y, z)

This can be defined to determine the weight of the scatter image reduction process in the normal pixel of the input image,

$$i_d(u,v) = \frac{\sum_{y,z} I(y,z) w(u,v,y,z)}{\sum_{y,z} w(u,v,y,z)}$$

From the above equation,
'i_d' denote the de-noised intensity of pixel '(u, v)'.

To improve the quality of images at the input, to proportionally raise the peak signal-to-noise ratio in the denoising process of nonlinear anisotropic diffusion is detailed in the algorithm described below.

Algorithm2:

// Non-Linear Anisotropic Diffusion Image Denoise FilteringAlgorithm
Input: image Database '$d = i_1, i_2, .. i_n$'
Output: Improves Image quality
Step 1:Begin
Step 2: **For** each image '$i \in d$'
Step 3: Apply the anisotropic diffusion model
Step 4: Apply a non-linear filter
Step 5: Compute the weight
Step 6: Perform the pixel intensity denoising with a weight value
Step 7: **End For**
Step 8: End

Non-Linear Anisotropic Diffusion Image Denoise Filtering is described in detail in Algorithm 2. This proposed approach significantly reduces noisy data in images and achieves higher image quality with the assistance of the algorithm mentioned above.

3.3 APPROXIMATE MULTIPLIER IN NEURAL NETWORK SYSTEM

The suggested approach appears to use an approximative multiplier, which in a neural network system consists of hundreds of thousands of multiplications, to reduce power consumption. Multilayer perception models can aid with accuracy by carrying out the impact of inaccurate multiplication on neural networks.

The output of inexact multiplier m is defined as
m (a, b) = (a, b) + Δ (a, b),
whereΔ is a jitter function.

When m is a function used to accurate multiplication value and no retraining is applied and accuracy of neural network is decreased.For the purpose of analysing the operation of a network system, the input operand for multiplication is zero. As a result, the random jitter's output value is non-zero, and this inaccuracy is multiplied. We concluded that the multiplication must be accurate if at least one of the operands is zero.

To redefined the multiplier has to be investigated following as,

$$m'(a, b) = \begin{cases} m(a,b), & if\ a,b \neq 0 \\ 0, & otherwise \end{cases}$$

3.4 DESIGN APPROXIMATE MULTIPLIER

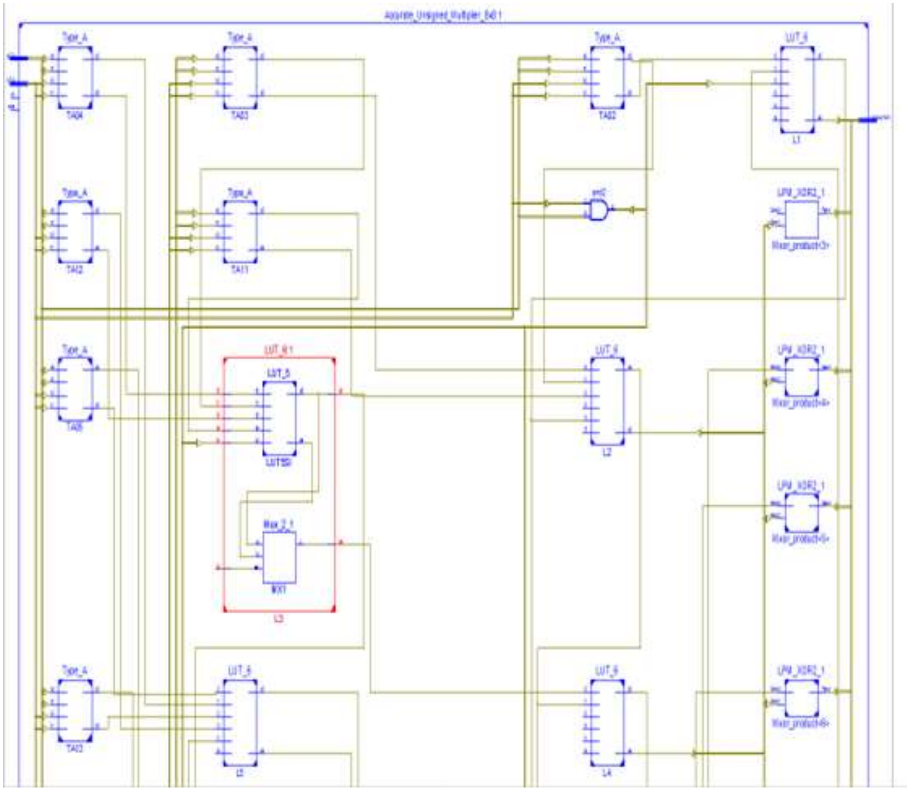

Figure3Approximate Multiplier Design

Figure 4 Original Image

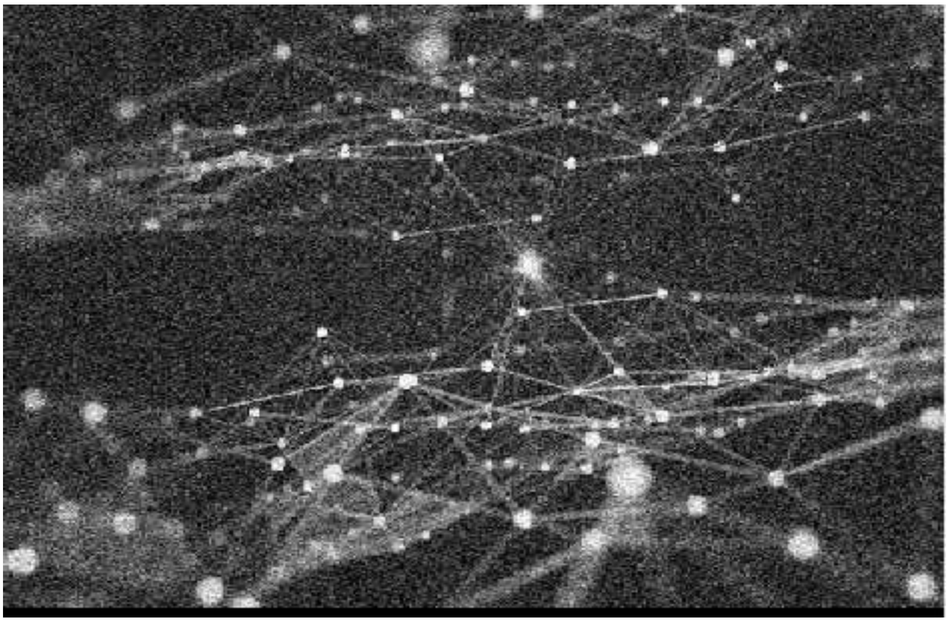

Figure5 Noisy Image

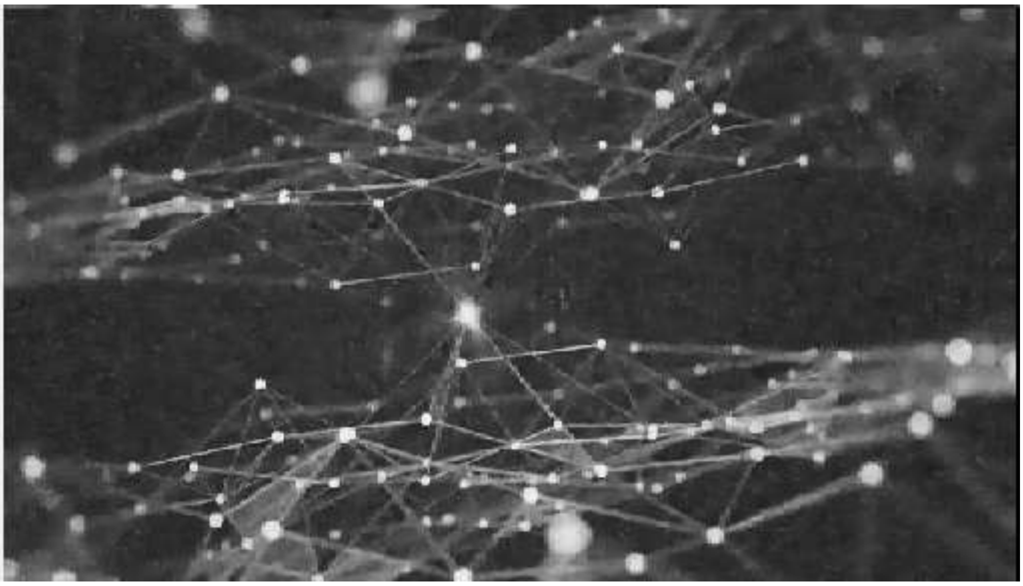

Figure6Denoised Image

3.5 MULTIPLICATIVE NOISE ALGORITHM

The traditional algorithm is to remove the additive noise but cannot remove the multiplicative noise. This paper proposes that denoising with the multiplicative noise has been removed.

For the additive model of denoising algorithm defined as,

$u0(x,y)=hd(x,y)*f(x,y)$.

Convolution changes in Fourier transform

$U(u,v)=Hd(u,v)\cdot F(u,v)$,

Logarithmic transformation function as

$\ln(u,v)=\ln F(u,v)+\ln Hd(u,v)$.

For additive denoising algorithm in partial differential equation

$\ln(u,v)=\ln F(u,v)$.

For exponential transform

$U(u,v)=F(u,v)$.

Inverse fast Fourier transform

$u=f$,

4. SIMULATION SETTINGS

The design FNNOAM-NLADID method analyses and runs MATLAB 2019a on a windows platform with an i4 intelcore CPU and 8GB RAM. This method involves an approximate multiplier and a novel approximate multiplier. The databasedepends on the volume of the pixel images in size. The proposed system evaluates the filtering time, peak signal-to-noise ratio, power consumption and speculative noise.

Peak signal-to-noise ratio

PSNRis defined as the original pixel value divided by the mean square error value. The difference between actual and denoising sizes represents the mean square error. The unit of the peak signal-to-noise ratio is the decibel(dB).

PSNR denotes the peak error, and it is calculated using the formula

$PSNR$ = 20 log10 ($MAXf/\surd MSE$)

Mean square error is defined as

$$MSE = [I_d - I_o]^2$$

Here,

MAXf – Maximum pixel images

MSE – Mean square error

I_d - Noise image

Io- Original image

Filtering time

Filtering time is represented as the multiplication of a number of input images and the time taken from the filter of the one-shot. The unit of filtering time in milliseconds.

$$T_F = I_n * time\ for\ filtering\ one\ image$$

Here,

I_n – No. of input images

Power consumption

Power consumption is defined as the subtraction of total power from the residual power. It is measured the unit is Watts.

$$P_C = T_P - R_P$$

Here,

T_P- Total power

R_p- Residual power

5. ANALYSIS OF PERFORMANCE

FNNOAM NLADID approaches performance is compared to those two approaches with the various multiplier.The comparison of the peak signal-to-noise ratiois based on the different input image sizes.

Table 1Evaluation of PSNR

Image size (KB)	Peak signal-to-noise ratio (dB)		
	FNNOAM NLADID method	**A design approach for the Approximation multiplier**	**Novel approximate compressor**
19	55.13	50.07	46.55
16	44.75	43.52	40.9
20	56.09	45.21	42.56
8.22	61.28	55.67	48.86
13.9	48.13	45.85	44.05
14.1	49.05	47.3	45.21

In Tab:1, two different approaches and the proposed method. The simulation result reduces the mean square value and increases the peak signal-to-noise ratio. The values were plotted in PSNR, shown in figure 7.

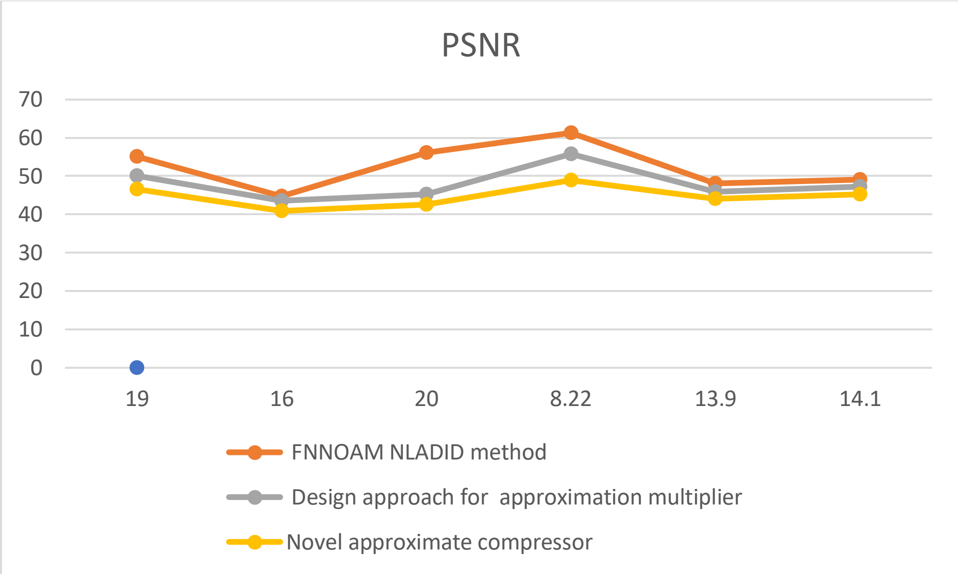

Figure 7Graphical representation of PSNR

The next one is filtering time, which aids in determining the suggested algorithm's efficiency from images. The number of images to be entered ranges from 10 to 50. Comparison of filtering time shown in Tab: 2

Table 2Comparision of filtering time

Number of Images (KB)	Filtering Time (ms)		
	FNNOAM-NLADID method	**A design approach for approximation multiplier**	**Novel approximate compressor**
10	23	34	43
20	27	36	46
30	30	39	49
40	32	41	51
50	35	44	54

The filtering time reduced the proposed method between the two approaches and plotted the graph shown in the figure.8

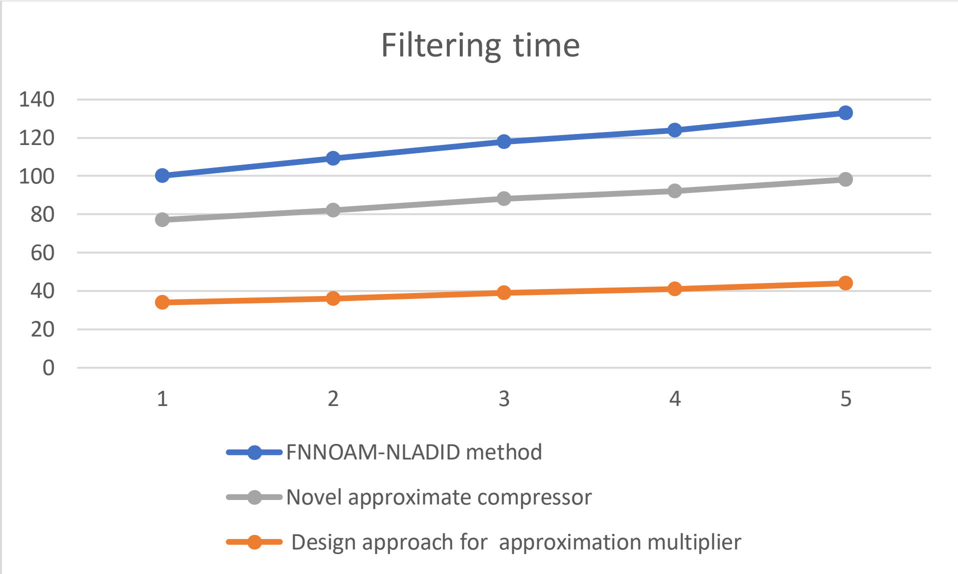

Figure 8 Graphical representation of filtering time

The third parameter is discussed, power consumption, to compare the two approaches. The two approaches are shown in values Tab:3. The values are plotted in a graph, as shown in the figure.9

Table 3 comparing power consumption

Method	Power Consumption (µW)
FNNOAM-NLADID method	988.10
A design approach for approximation multiplier	1247.56
Novel approximate compressor	1345.87

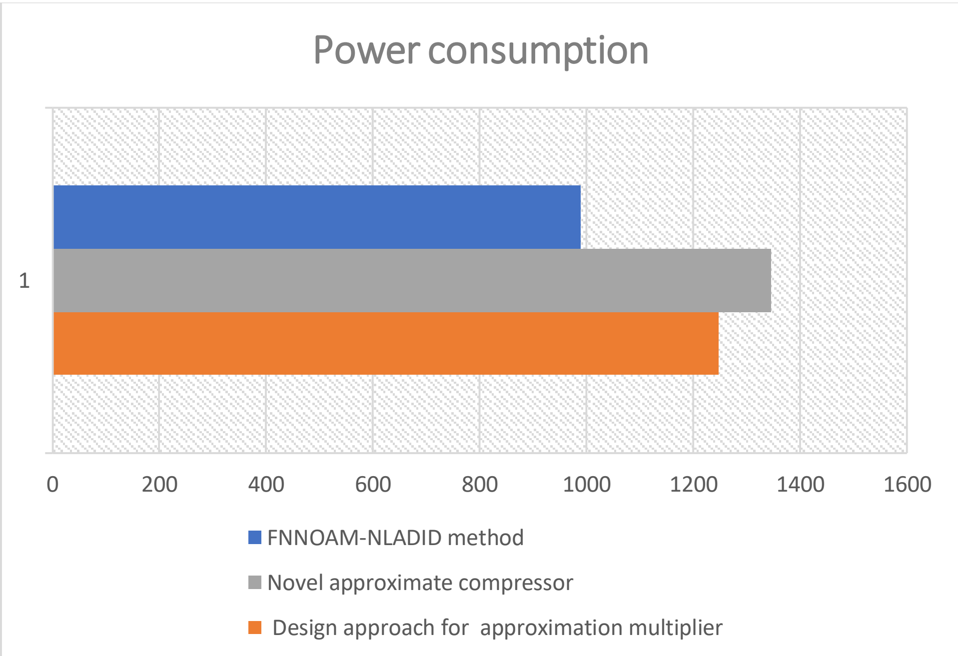

Figure9Graphical representation of power consumption

6. **CONCLUSION**

Multipliers are an essential component of many digital systems. Approximation multipliers have become increasingly crucial in microprocessors as technology has advanced. TheFNNOAM-NLADID Method is given to reduce noise in input imagesand also reduces power consumption, multiplicative noise and design complexity. Using fuzzy neural network optimization, the FNNOAM -NLADID technique is employed to select the optimal component multiplier design for the building approximation approach. A fuzzy neural network system based on power consumption and design complexity is decreased by choosing appropriate components. The image denoising technique is used to eliminate noise artefacts from input images and enhance the excellent performance image quality once the approximation multiplier is created. The power consumption and design complexity were lowered due to the fuzzy neural network technology.The simulation analysis for several metrics with a number of input images has been recorded. According to the findings, this proposed method achieves good results in relationships of efficient design of approximation multiplier with low filtering time and power consumption. The fuzzy neural network system also reduces the multiplicative noise and complicated input and output values.

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