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Image Focus Measure by Wavelet Transform with Gaussian Derivative and Spatial Frequency and Image Enhancement using Fuzzy Logic

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ABSTRACT

In this paper, focus measure of blurred and noisy images is computed with the help of Discrete Wavelet Transform with Gaussian Derivative (DWTGDR) technique and Discrete Wavelet Transform with Spatial Frequency (DWTSF) technique at 4th wavelet decomposition level. A Discrete Wavelet Transform is a robust method for approximating the blurred and noisy image data carried out by the image itself. This blurred image degradation effects on a neighborhood of the data within the image. The aim of image focus measurement is to prove that as the image becomes more and more defocused, the focus measure goes on decreasing. Another objective in this paper is to enhance the defocused images for further processing like depth estimation, 3D visualization, etc. Daubechies Wavelet Transform is used for computing wavelet coefficients up to three decomposition levels. At wavelet decomposition level 4, Daubechies Wavelet Transform along with GDR and SF is employed to compute wavelet coefficients. We analyzed that the wavelet coefficients monotonically decreased with increase in blur and noise in the image. Further, that defocused image is enhanced with the employed method of Deep Neural Network with Fuzzy Membership Function.

Key words: Crisp Set, Fuzzy Membership Function, Deep Neural Network, Gaussian Derivative, Spatial Frequency, Focus Measure.

1. INTRODUCTION

When a television has invented, there are many evolutions, from black-and-white to color. Also, high-resolution television is more popular, now a days, in the market. The growth of 3D television system has grabbed more attention.
The camera captures an image in 2D picture form. Sometimes, the image may be blur or noisy due to many reasons. To process them further, it is important to enhance them. Hence, some literature survey is presented.
The remaining part of this paper is arranged as follows: Section II describes Background of Discrete Wavelet Transform, Gaussian Derivative and Spatial Frequency. Section III presents some observations and results of the proposed DWTGDR and DWTSF. Section IV describes Background of Fuzzy Membership Function. Section V presents proposed methodology of Deep Neural Network with Fuzzy Logic, section VI describes steps in proposed Fuzzy Membership Function. Section VII describes some experimental results of a proposed Fuzzy Logic with Deep Neural Network. Finally, Section VIII gives the conclusion.

Kautsky, and other authors, in paper [1], presented a novel focus measure of images based on Discrete Wavelet Transform. They computed wavelet coefficient which is a division of High pass band to Low pass band. The authors proved that the focus measure is monotonic with the degree of defocus and it is robust. The experimental results are computed up to wavelet 2nd decomposition level.
Jain Atika and other authors, in paper [2], employed a method of a focus measure of images that is grounded on a wavelet transform of an image. The authors argued an effect of various Daubechies filters in wavelet and image decomposition levels up to 4. That image is later recreated with inverse DWT. The results express that the wavelet coefficients behaves randomly at level 4.
Atika Jain, K M Singh, S Prabhakar Rao, in paper [3], presented a method of decomposition of image and focus measurement on wavelet w. the detailed elements of image are computed up to level-4. The results show that the wavelet coefficients behaves randomly at level 4 also.
Xin Yi, Mark Eramian, in paper [4], presented a metric of sharpness depending upon Local Binary Patterns. A robust algorithm of segmentation used to isolate in focus and out of focus image sections. There experimental results show that most of the local blurry regions patches have significantly fewer of certain local binary patterns as compared to the regions in the sharp.
M A Rahman, in paper [5], used multi focus image fusion technique along with focus measure as well as Fuzzy Logic. Focus measure depending upon sum of Gradients is employed in this paper.
Murali Subbarao, Tae Choi and Arman Nikzad, in paper [6], proposed an image formation model named Paraxial

Geometric Optics for deriving some camera focusing methods. These methods are executed on one model system named the SPARCS. The energy of low-pass-filtered image gradient is recommended.

Cuong, in their paper [7], used spectral and spatial characteristics of an image. The measures give a supposed sharpness model where larger values denote perceptually sharper areas. Results show that S3 maps are extremely related on the basis of maps of a sharpness.

Varun Srivastava, Ravindra Kumar Purwar, in paper [8], proposed a 2D wavelet based decomposition method for grouping biomedical images. One feature set is created and later, it minimized by PCA (Principal Component Analysis). The set is later provided to *K* Nearest Neighbor Technique or Feed Forward ANN, to categorize the pictures.

C M Sheela Rani, in paper [9], proposed a Feature level Wavelet Transform which is based on Block with Neural Network i.e. BFWN model for an image fusion. The derived model is differentiated with Discrete Wavelet Transform to evaluate the output image quality. The observations claim that the derived model is very efficient and feasible for the fusion of image.

Jyoti Kulkarni, Manna Sheela Rani Chetty, in paper [10], the proposed work is based on image restoration, if it is blurry and noisy. The image focus measured based on DWT and then recovered using recovery algorithms in the presence of motion and Gaussian blur. The results are later compared depending on the performances.

Samrudh K, Sandeep Joshi, in paper [11], proposed an image enhancement method for improving the quality by considering a contrast as major feature. Previous approaches of contrast enhancement e.g. histogram equalization marks in more or less enhancement in a lower resolution. The authors in Paper [11] goal in emerging a novel Fuzzy Inference System for enhancing the contrast of the images with low resolution which overcome the limitations of the traditional techniques.

Praveen K Shetty, V S Veena Devi, in paper [12], proposed an image enhancement based on Mamdani's Fuzzy Inference System. On the original image, some fuzzy Rules are applied and later a defuzzification is applied on it so that enhance image can be obtained. Further, MSE (Mean Square Error) and PSNR (Peak Signal to Noise Ratio) have been computed.

Dillip Nayak, Ashutosh Bhoi, in paper [13], proposed to use Fuzzy Logic and Fuzzy Sets with some morphological operations to enhance the contrast of images. A modified membership function has been used to fuzzify the image. The produced images are compared with the proposed technique.

Tarun Mahashwari, Amit Asthana, in paper [14], presented a Fuzzy Method that enhances an image.

Jae Il Jung, Yo Sung Ho, in paper [15], proposed one novel Depth Estimation technique that uses an object classification of an image based on one learning called Bayesian Learning. This method uses six attributes of the training data and the authors [15] classified the single view image objects in four different categories.

Harel Haim and others, in paper [16], proposed a method for estimation of a depth of an image using an aperture camera which is phase coded. This camera delivers some color characteristics which are unambiguous and depth- related for an image which is captured.

K G Shreyas Dixit, in paper [17], argues on YOLO (You only look once), a robust characteristic of CNN which becomes with an entirely different method of understanding the task of objects detection.

Jyoti B. Kulkarni, Manna Sheela Rani Chetty, in paper [18], considered indoor images with different objects. Then the focus measures of all objects in the images have been computed using Discrete Wavelet Transform.

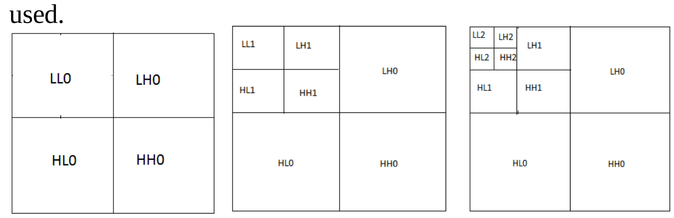
Sandeep D. Pande, in paper [19], proposed a method for retrieval of an image based on Cubic Bezier Curve to find similarity of each image in the database.

Sandeep D. Pande, in paper [20], employed leaf classification method using CapNet. Leaf image features are extracted here.

2. BACKGROUND OF DISCRETE WAVELET TRANSFORM (DWT), GAUSSIAN DERIVATIVE AND SPATIAL FREQUENCY

2.1 Discrete Wavelet Transform

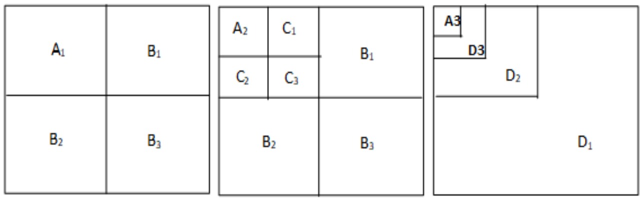
Discrete Wavelet Coefficient is defined as high pass band and low pass band norms ratio. Low frequency coefficient gives important information and smoothness in image. High frequency coefficients give roughness. DWT can be used to find focus measure of image in terms of wavelet coefficient. Many transform like Discrete Cosine Transform, Continuous Wavelet Transform, Discrete Wavelet Transform are available. But DWT gives better compression ratio. DCT offers lossy transform, but DWT offers both lossy as well as lossless transform. In the proposed scope, lossless DWT is used.



(a) (b) (c)

Figure 1: (a) wavelet decomposition level 1 (b) wavelet decomposition level 2 (c) wavelet decomposition level 3

In Figure 1, DWT decomposes an image into four bands which are frequency bands called Low-High (LH), Low-Low (LL), High-High (HH) and High-Low (HL) and it decomposes the image with each level that corresponds to a band called coarser resolution band.



(a) (b) (c)

Figure 2: Wavelet Decomposition coefficients

In Figure 2 (a), A1 is an approximation of the original image, B1 is a detailed sub image containing horizontal component, B2 is a detailed sub image containing vertical component and B3 is a detailed sub image containing diagonal component of the original image.

$$w = \frac{\|hw\ (f)\|}{\|lw\ (f)\|} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

Where, w is a wavelet coefficient, f is an image of size Nr number of rows and Nc number of columns. $\|.\|$ Shows Euclidean Norm.

Wavelet Focus Measure w is the quantitative relation of high frequency to low frequency coefficients. For computing hw(f), Bi coefficients of the level, are considered. For computing lw(f), Ai coefficients of the level, is considered.

As we increase blur amount, focus coefficient (w) goes on decreasing. It is monotonous to blur parameter. If number of decomposition levels is increased, then after some threshold, wavelet coefficient w increases. If there is increase in the levels of decomposition of Discrete Wavelet Transform, after some threshold, coefficient w increases.

2.2 Gaussian Derivative:

It is an approach to find focus measure of an image.

$$\sigma^2 = \frac{1}{X \times Y}\sum_{p=1}^{X}\sum_{q=1}^{Y}(I_1(p,q) - (\frac{1}{X \times Y}\sum_{p=1}^{X}\sum_{q=1}^{Y} I_1(p,q))$$

Where σ is standard deviation of Image I_1, I_1 is an image of size XxY.

$$G_x = e^{-(x^2/2\times\sigma^2)},$$

$$G_y = e^{-(y^2/2\times\sigma^2)} \qquad \text{; Where x and y are grids of size NxN}$$

$$G_{(x,\sigma)} = \frac{-x}{\sigma^2} \times G_x \qquad \ldots\ldots\ldots\ldots\text{x derivative}$$

$$G_{(y,\sigma)} = \frac{-x}{\sigma^2} \times G_y \qquad \ldots\ldots\ldots\ldots\text{y derivative}$$

$$R_x(p,q) = \sum_{i=1}^{M}\sum_{j=1}^{N} I_1(p+i-1, q+j-1) \times G_{(x,\sigma)}(i,j) \text{ ; Where kernel G is of size MxN.}$$

$$R_y(p,q) = \sum_{i=1}^{M}\sum_{j=1}^{N} I_1(p+i-1, q+j-1) \times G_{(y,\sigma)}(i,j) \text{ ; Where kernel G is of size MxN.}$$

$$FM = mean\ (R_x^2 + R_y^2) \qquad \text{; Where FM is focus measure}$$

2.3 Spatial Frequency

Spatial Frequency (SF) of Image I1 of size $X \times Y$ computes an activity level in that image. It is referred to compute changes in the frequency along the columns and rows, i.e. it is used for calculating focus measure of an image.

$$RowFrequency(RF) = \sum_{p=1}^{X}\sum_{q=1}^{Y}\sqrt{(I_1(p,q) - I_1(p,q-1)^2)}$$

$$ColumnFrequency(CF) = \sum_{p=1}^{Y}\sum_{q=1}^{X}\sqrt{(I_1(p,q) - I_1(q-1,p)^2)}$$

$$SpatialFrequency(SF_1) = \sqrt[2]{RF^2 + CF^2}$$

2.4 Schematic Block Diagram of proposed Discrete Wavelet Transform with Gaussian Derivative (DWTGDR)

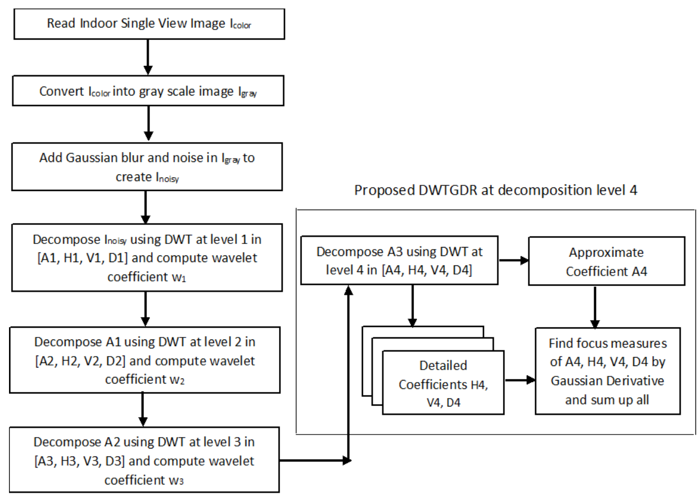


Figure 3: Schematic Block Diagram of proposed Discrete Wavelet Transform with Gaussian Derivative (DWTGDR)

2.5 Schematic Block Diagram of proposed Discrete Wavelet Transform with Spatial Frequency (DWTSF)

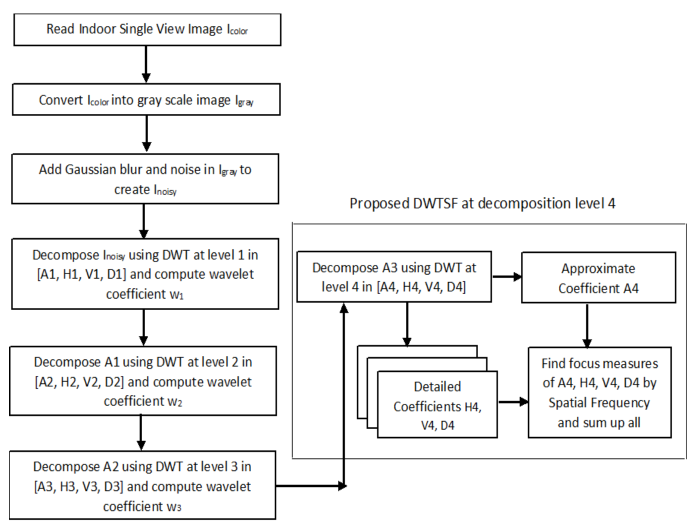


Figure 4: Schematic Block Diagram of proposed Discrete Wavelet Transform with Spatial Frequency (DWTSF)

2.6 Algorithms of the Proposed Techniques

2.6.1 Algorithm of proposed Discrete Wavelet Transform with Gaussian Derivative (DWTGDR):

1. Read colour image $I_{colored}$ of size MxN.
2. Convert $I_{colored}$ into I_{gray} and convert into double $I_{graydouble}$ of size MxN.
3. Loop iterations i=1:5 do

   3.1 Add Gaussian noise g(i, j) in $I_{graydouble}$ and apply [9x9] pixel mask with Gaussian blur to make it $I_{blurrednoisy;}$

   $$g(i,j) = \frac{1}{\sigma^2(2\pi)}\left(e^{\frac{-(j^2+i^2)}{2\sigma^2}}\right)$$

   Where, σ is Standard Deviation of Gaussian Distribution from centre, *i* is a distance in horizontal axis from the origin and *j* is the distance in vertical axis from the origin.

   3.2 loop DWT decomposition level j=1:3 do

   a) Apply db10 on $I_{blurrednoisy}$ to obtain A_j, H_j, V_j, D_j; where A_j, H_j, V_j, D_j are approximation, horizontal, vertical and diagonal coefficients respectively.

   b) Compute,

   $$A_{j1} = \sum_{i=1}^{x}(\sum_{k=1}^{y}(abs(A_j(i,k)^{\wedge}2))^{1/2}$$

   Where, x and y are rows and columns of A_j

   c) Compute,

   $$H_{j1} = \sum_{i=1}^{x}(\sum_{k=1}^{y}(abs(H_j(i,k)^{\wedge}2))^{1/2}$$

   Where, x and y are rows and columns of H_j

   d) Compute,

   $$V_{j1} = \sum_{i=1}^{x}(\sum_{k=1}^{y}(abs(V_j(i,k)^{\wedge}2))^{1/2}$$

   Where, x and y are rows and columns of V_j

   e) Compute,

   $$D_{j1} = \sum_{i=1}^{x}(\sum_{k=1}^{y}(abs(D_j(i,k)^{\wedge}2))^{1/2}$$

   Where, x and y are rows and columns of D_j

   f) Compute,

   $$B_0 = (\sum_{l=1}^{y}(H_{j1}) + (\sum_{l=1}^{y}(V_{j1}) + (\sum_{l=1}^{y}(D_{j1})$$

   g) Compute,

   $$A_0 = (\sum_{l=1}^{y}(A_{j1})$$

   h) Compute wavelet coefficient $w_j = B_0/A_{0\,;}$

   End Loop.

4. At decomposition level 4,
   1. Apply db10 on A_3 to obtain A_4, H_4, V_4, D_4; where A_4, H_4, V_4, D_4 are approximation, horizontal, vertical and diagonal coefficients respectively.
   2. Compute Gaussian Derivative (GDR) on A_4 and compute focus measure $GDR_{1.}$
   3. Repeat step 2 for H_4, V_4, D_4 and compute GDR_2, GDR_3, and GDR_4 respectively.
   4. Focus measure GDR= abs(GDR_1 + GDR_2 + GDR_3 + GDR_4)
5. End loop
6. Analyse the decrease in w_4 at level 4 with the proposed scheme of DWTGDR.

2.6.2. Algorithm of proposed Discrete Wavelet Transform with Spatial Frequency (DWTSF):

1. Read colour image $I_{colored}$ of size MxN.
2. Convert $I_{colored}$ into I_{gray} and convert into double $I_{graydouble}$ of size MxN.
3. Loop iterations i=1:5 do

   3.1 Add Gaussian noise in $I_{graydouble}$ and apply [9x9] pixel mask with Gaussian blur to make it $I_{blurrednoisy;}$

   $$g(i,j) = \frac{1}{\sigma^2(2\pi)}\left(e^{\frac{-(j^2+i^2)}{2\sigma^2}}\right)$$

   Where, σ is Standard Deviation of Gaussian Distribution from centre, *i* is a distance in horizontal axis from the origin and *j* is the distance in vertical axis from the origin.

   3.2 Loop DWT decomposition level j=1:3 do

   a) Apply db10 on $I_{blurrednoisy}$ to obtain A_j, H_j, V_j, D_j; where A_j, H_j, V_j, D_j are approximation, horizontal, vertical and diagonal coefficients respectively.

   b) Compute,

   $$A_{j1} = \sum_{i=1}^{x}(\sum_{k=1}^{y}(abs(A_j(i,k)^{\wedge}2))^{1/2}$$

   Where, x and y are rows and columns of A_j

   c) Compute,

   $$H_{j1} = \sum_{i=1}^{x}(\sum_{k=1}^{y}(abs(H_j(i,k)^{\wedge}2))^{1/2}$$

   Where, x and y are rows and columns of H_j

   d) Compute,

   $$V_{j1} = \sum_{i=1}^{x}(\sum_{k=1}^{y}(abs(V_j(i,k)^{\wedge}2))^{1/2}$$

   Where, x and y are rows and columns of V_j

   e) Compute,

   $$D_{j1} = \sum_{i=1}^{x}(\sum_{k=1}^{y}(abs(D_j(i,k)^{\wedge}2))^{1/2}$$

   Where, x and y are rows and columns of D_j

   f) Compute,

   $$B_0 = (\sum_{k=1}^{y}(H_{j1}) + (\sum_{k=1}^{y}(V_{j1}) + (\sum_{k=1}^{y}(D_{j1})$$

   g) Compute,

   $$A_0 = (\sum_{k=1}^{y}(A_{j1})$$

   h) Compute wavelet coefficient $w_j = B_0/A_{0\,;}$

   End Loop.

4. At decomposition level 4,
   1. Apply db10 on A_3 to obtain A_4, H_4, V_4, D_4; where A_4, H_4, V_4, D_4 are approximation, horizontal, vertical and diagonal coefficients respectively.
   2. Compute Spatial Frequency (SF) on A_4 and compute focus measure $SF_{1.}$

      Row Frequency =

      $$RF = \sum_{i=1}^{x}\sum_{k=1}^{y}\sqrt{(A_4(i,k) - A_4(i,k-1)^2)}$$

      Column Frequency =

      $$CF = \sum_{i=1}^{y}\sum_{k=1}^{x}\sqrt{(A_4(i,k) - A_4(k-1,i)^2)}$$

      $$SpatialFrequency(SF_1) = \sqrt[2]{RF^2 + CF^2}$$

   3. Repeat step 2 for H_4, V_4, D_4 and compute SF_2, SF_3, and SF_4 respectively.
   4. Focus measure FM= abs(SF_1 + SF_2 + SF_3 + SF_4)
5. End loop
6. Analyse the decrease in w_4 at level 4 with the proposed scheme of DWTSF.

3. EXPERIMENTAL RESULTS

(a) (b) (c) (d)

Figure 5: (a) Original color image (b) original gray scale image (c) image with blur and noise in iteration 1 (d) image with more blur and noise in iteration 2

Table 1: Results of existing approach of DWT for images in Figure 5

Image size (512x512)	w1 (level 1)	w2 (level 2)	w3 (level 3)	w4 (level 4)
Iteration 1	0.2923	0.1596	0.1277	0.147
Iteration 2	0.2935	0.153	0.1195	0.1467
Iteration 3	0.2953	0.1531	0.1163	**0.1499**
Iteration 4	0.2952	0.1531	0.1144	**0.1489**
Iteration 5	0.2957	0.1529	0.1134	**0.1498**

In Table 1, in 5 iterations, wavelet coefficients are computed in 4 decomposition levels. The results at level 4 show that the wavelet coefficients w4 goes on increasing using DWT for the images shown in Figure 5.

Table 2: Results of existing approach with DWT with SF for images in Figure 5

Image size (512x512)	w1 (level 1)	w2 (level 2)	w3 (level 3)	Focus Measure (DWT with SF at level 4)
Iteration 1	0.2923	0.1596	0.1277	**0.1211**
Iteration 2	0.2935	0.153	0.1195	**0.1177**
Iteration 3	0.2953	0.1531	0.1163	**0.1166**
Iteration 4	0.2952	0.1531	0.1144	**0.1161**
Iteration 5	0.2957	0.1529	0.1134	**0.1161**

In Table 2, in 5 iterations, wavelet coefficients are computed in 4 decomposition levels. The results at level 4 show that the wavelet coefficients w4 goes on decreasing using proposed DWTSF technique for the images shown in Figure 5.

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Table 3: Results of existing approach with DWT with GDR for images in Figure 5

Image size (512x512)	W1 (level 1)	W2 (level 2)	W3 (level 3)	Focus Measure (DWT with GDR at level 4)
Iteration 1	0.2923	0.1596	0.1277	0.0875
Iteration 2	0.2935	0.153	0.1195	0.0907
Iteration 3	0.2953	0.1531	0.1163	**0.0864**
Iteration 4	0.2952	0.1531	0.1144	**0.0767**
Iteration 5	0.2957	0.1529	0.1134	**0.0611**

In Table 3, in 5 iterations wavelet coefficients are computed in 4 decomposition levels. The results at level 4 show that the wavelet coefficients w4 goes on decreasing using proposed DWTGDR technique for the images shown in Figure 5.

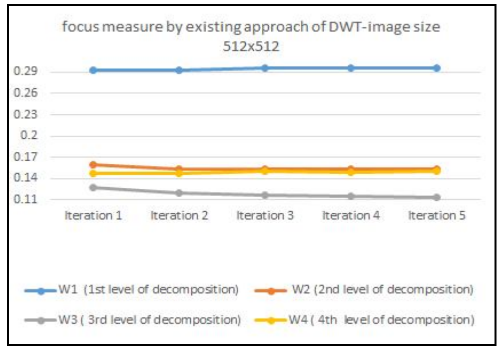


Figure 6: Focus Measure by DWT Technique for Table 1

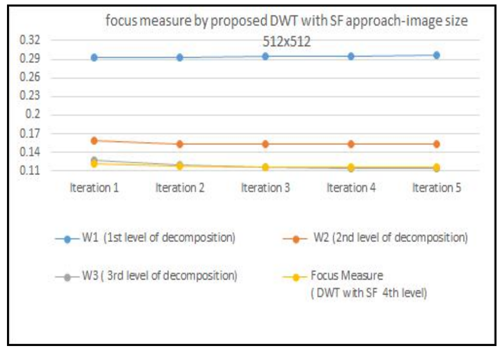


Figure 7: Focus Measure by DWT Technique for Table 2

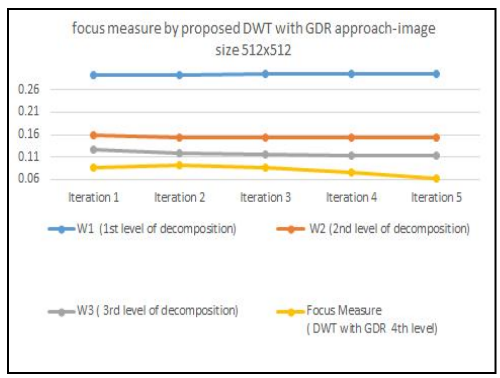
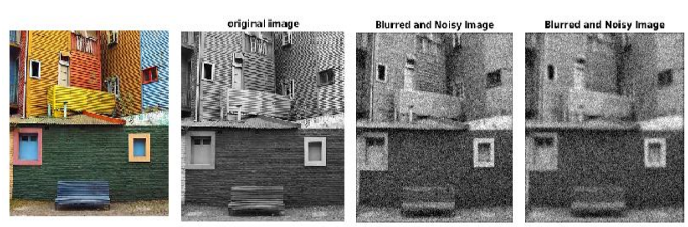


Figure 8: Focus Measure by DWT with GDR Technique for Table 3

The graphical results in Figure 6, Figure 7 and Figure 8 show that as the noise and blur amount increased in every iteration from 1 to 5, the proposed algorithms compute focus measures which go on decreasing as compared to existing work [2], [3].



(a) (b) (c) (d)

Figure 9: (a) Original color image (b) original gray scale image (c) image with blur and noise in iteration 1 (d) image with more blur and noise in iteration 2

Table 4: Results of existing approach of DWT for images in Figure 9

Image size (300x309)	W1 (level 1)	W2 (level 2)	W3 (level 3)	W4 (level 4)
Iteration 1	0.3307	0.2068	0.1713	0.217
Iteration 2	0.3328	0.1786	0.1512	0.2146
Iteration 3	0.3337	0.1747	0.1433	**0.215**
Iteration 4	0.3352	0.1759	0.1406	**0.2185**
Iteration 5	0.3367	0.1758	0.1426	0.2145

In Table 4, in 5 iterations, wavelet coefficients are computed in 4 decomposition levels. The results at level 4 show that the wavelet coefficients w4 goes on increasing using DWT for the images shown in Figure 9.

Table 5: Results of existing approach with DWT with GDR for images in Figure 9

Image size (300x309)	W1 (level 1)	W2 (level 2)	W3 (level 3)	Focus Measure (DWT with GDR at level 4)
Iteration 1	0.3307	0.2068	0.1713	**0.1732**
Iteration 2	0.3328	0.1786	0.1512	**0.1613**
Iteration 3	0.3337	0.1747	0.1433	**0.1528**
Iteration 4	0.3352	0.1759	0.1406	**0.1397**
Iteration 5	0.3367	0.1758	0.1426	**0.1119**

In Table 5, in 5 iterations, wavelet coefficients are computed in 4 decomposition levels. The results at level 4 show that the wavelet coefficients w4 goes on decreasing using DWTGDR for the images shown in Figure 9.

Table 6: Results of existing approach with DWT with SF for images in Figure 9

Image size (300x309)	W1 (level 1)	W2 (level 2)	W3 (level 3)	Focus Measure (DWT with SF at level 4)
Iteration 1	0.3307	0.2068	0.1713	**0.1192**
Iteration 2	0.3328	0.1786	0.1512	**0.114**
Iteration 3	0.3337	0.1747	0.1433	**0.1112**
Iteration 4	0.3352	0.1759	0.1406	**0.1108**
Iteration 5	0.3367	0.1758	0.1426	**0.1103**

In Table 6, in 5 iterations, wavelet coefficients are computed in 4 decomposition levels. The results at level 4 show that the wavelet coefficients w4 goes on decreasing using DWT for the images shown in Figure 9.

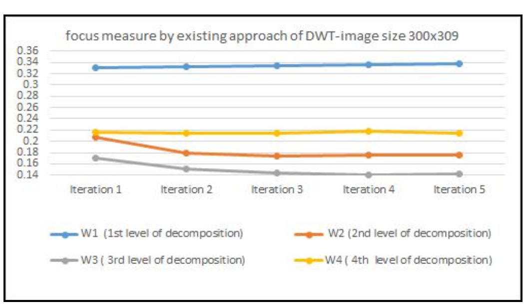


Figure 10: Focus Measure by DWT Technique for Table 4

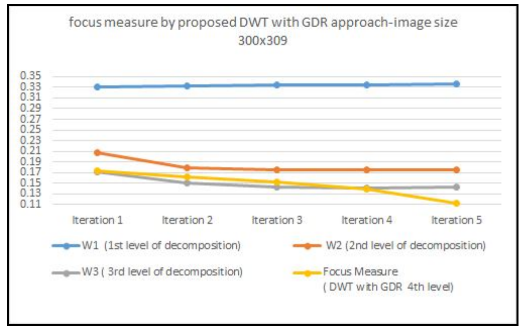


Figure 11: Focus Measure by DWT with GDR method for Table 5

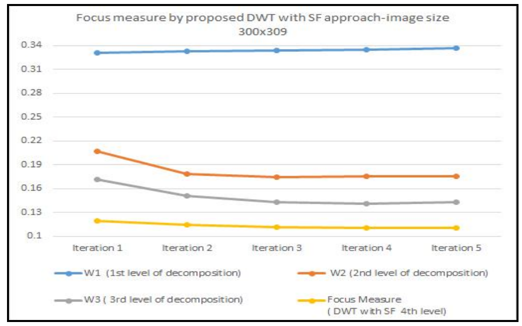


Figure 12: Focus Measure by DWT with SF method for Table 6

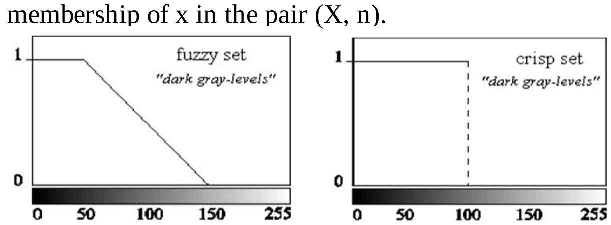
The graphical results in Figure 10, Figure 11 and Figure 12 show that as the noise and blur amount increased in every iteration from 1 to 5, the proposed algorithms compute focus measures which go on decreasing as compared to existing work [2], [3].

4. BACKGROUND OF FUZZY LOGIC

Many images which have low resolution, with some blur and noise. Fuzzy Logic shows important role in image restoration and enhancement. No as such any fixed strategy of image enhancement, but judgement can be done that how particular method can work properly. There are many image enhancement methods like spatial, frequency and fuzzy.

Image enhancement based on Fuzzy Inference System does mapping of gray level values to a fuzzy plane based on Membership Transformation Function. Fuzzy Logic is flexible, tolerant of imprecise data over Crisp Logic. Fuzzy Logic is a procedure of multiple valued logic which has the values in between 0 and 1.

Fuzzy Set is a pair (X, n), where X is a set and n: $X \to [0,1]$; for each, x∈X, where, mf(x) is referred as the degree of membership of x in the pair (X, n).



(a) (b)

Figure 13: (a) Representation of "dark-gray levels" with Fuzzy set (b) Representation of "dark-gray levels" with Crisp set

5. PROPOSED METHODOLOGY OF DEEP NEURAL NETWORK WITH FUZZY MEMBERSHIP FUNCTION

Step 1: Deep Neural Network Training

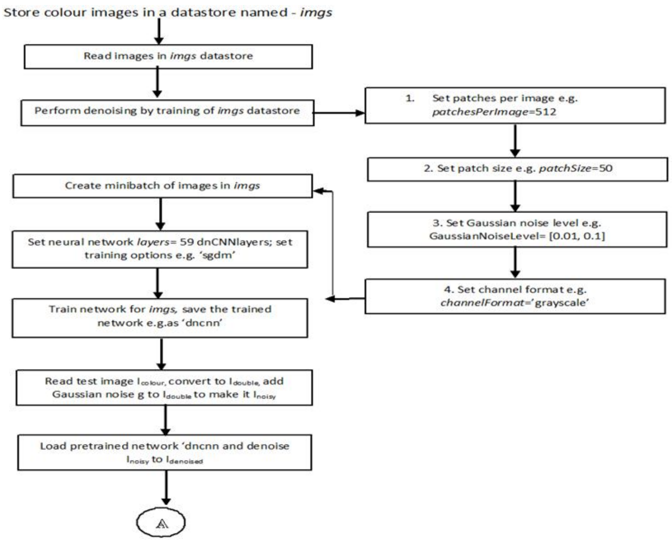


Figure 14: Block Diagram of Proposed Neural Network Training of images

Step 2: Image Enhancement

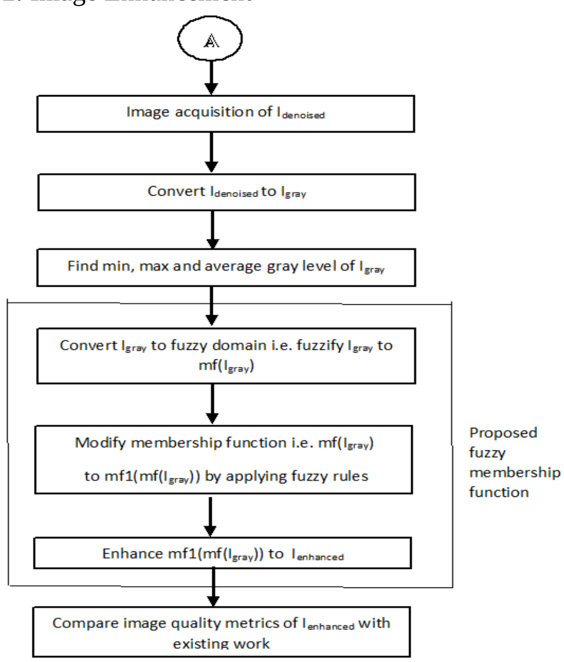
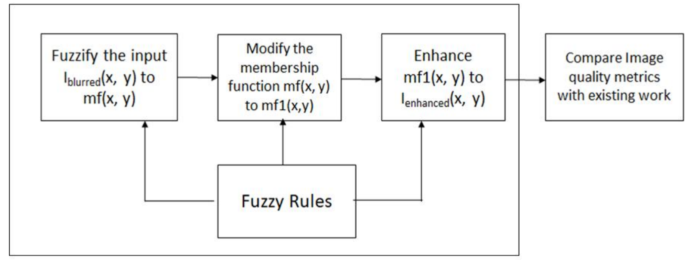


Figure 15: Block Diagram of Image Enhancement using Proposed Fuzzy Membership Function



Proposed Fuzzy Membership Function

Figure 16: Block Diagram of proposed Fuzzy Membership Function

Step 1: Deep Neural Network Training

Algorithm of Neural Network training:

1. Read training images in *imgs* datastore.
2. Perform denoising by training of *imgs* datastore;
   2.1 Set patches per image e.g. *patchesPerImage*=512,
   2.2 Set patch size e.g. *patchSize*=50,
   2.3 Set Gaussian noise level e.g. GaussianNoiseLevel = [0.01, 0.1],
   2.4 Set channel format e.g. *channelFormat* ='grayscale'.
3. Create minibatch of images in *imgs.*
4. Set neural network *layers*= 59 *dnCNNlayers*; Set training options as 'sgdm'; where 'sgdm' is Stochastic Gradient Descent with Momentum.
5. Train network for *imgs*, save the trained network e.g.as 'dncnn'.

6. Read test image $I_{colour,}$ convert to $I_{double,}$ add Gaussian noise g to I_{double} to make it $I_{noisy.}$
7. Load pretrained network 'dncnn and denoise I_{noisy} to $I_{denoised.}$
8. Provide $I_{denoised}$ to proposed fuzzy membership function to fuzzify.
9. End.

Step 2: Image Enhancement using proposed Fuzzy Membership Function

Algorithm of Proposed Fuzzy Membership Function:

1. Acquire image $I_{denoised}$.
2. Compute max, min and avrage gray level values of $I_{denoised..}$
3. Convert $I_{denoised}$ in fuzzy domain;
   3.1 Compute membership function
   $$mf\,(i,j) = c[(1+\alpha)^{I_{denoised}(i,j)} - 1];$$
   where, c is a constant, α is a factor responsible for pixel darkness and brightness, i & j are row and column index of images of size $M \times N$, respectively.
4. Modify membership function *mf(i, j)*;
   loop i=1 to M do

loop j=1 to N do

$$mf_{new}(i,j)=\begin{cases}3\times mf(i,j)^2; if\,(0\le mf(i,j)\le 0.33)\\ mf(i,j); if\,(0.33< mf(i,j)\le 0.5)\\ 1-2(1-mf(i,j))^2; if\,(0.5< mf(i,j)\le 1)\end{cases}$$

End loop
End loop

5. Compute $I_{enhanced}$ image
loop i=1 to M do
loop j=1 to N do
$I_{enhanced}(i, j) = c*log(1+ mf_{new}(i, j))$;
where, c is a constant responsible for change in pixel value.
End loop
End loop
6. Compute image quality metrics PSNR, IEF, MAE, MSE, SSIM of $I_{enhanced}$ (x, y).
7. Compare results with existing work.
8. End.

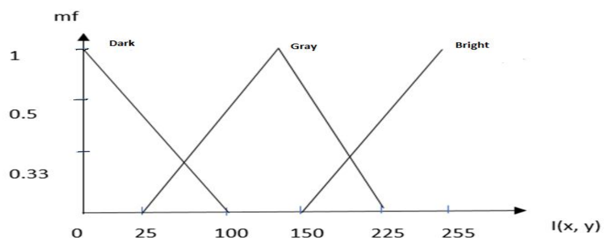


Figure 17: Image Pixels *I(i, j)* and triangular membership function *mf*

6. STEPS IN PROPOSED FUZZY MEMBERSHIP FUNCTION

A. Fuzzification of an input image:

Fuzzification is a theory of allocating essential membership function on an image that converts the image to fuzzy domain from gray level pixel domain. Fuzzy sets have distinctive membership functions with distinctive situations which are called as characteristic functions in crisp sets. The developed defocused color image is converted to a membership plane by applying membership function where its pixels are in the range of 0 to 1. The function considers infinite values between the range of 0 to 1. In my proposed Fuzzy Membership Function, a triangular function is employed to convert the image from pixel domain to membership domain.

To convert $I_{denoised}$ image into fuzzy domain, exponential transformation is used.

$$mf(i,j)=c[(1+\alpha)^{I_{denoised}(i,j)}-1]=e^{I_{denoised}(i,j)}$$

Where, c is a constant, α is a factor responsible for pixel darkness and brightness, x & y are row and column index of images of size $M\times N$ respectively.

B. Modification of membership function:

The objective of modification of the membership function is to modify the gray value of the image in fuzzy domain. The dark pixels in the fuzzy range of 0 to 0.33 are darkened more. The gray pixels in the range greater than 0.33 to 0.5 are kept same. The gray pixels in the range greater than 0.5 to 1 are brightened more.

C. Enhance the modified image:

Logarithmic transformation is applied on $mf_{new}(i, j)$.

$I_{enhanced}(i, j) = c*log(1+ mf_{new}(i, j))$;

Where, c is a constant and responsible for change in pixel value. As we go on increasing C, bright pixels become brighter.

D. Image Quality Metrics:

$I_{enhanced}(i, j)$ is compared with existing work by comparing the following image quality metrics.

$$MAE=\sum_{x=1}^{M}\sum_{y=1}^{N}\frac{|I(x,y)-I_1(x,y)|}{M\times N}$$

$$MSE=\sum_{x=1}^{M}\sum_{y=1}^{N}\frac{(I(x,y)-I_1(x,y))^2}{M\times N}$$

$$PSNR\,(dB)=10\times\log_{10}(\frac{255^2}{MSE})$$

$$IEF=\frac{\sum_{x=1}^{M}\sum_{y=1}^{N}(\eta(x,y)-I(x,y))^2}{\sum_{x=1}^{M}\sum_{y=1}^{N}(I_1(x,y)-I(x,y))^2}$$

$$SSIM(x,y)=[l(x,y)]^{\alpha}\,.\,[c(x,y)]^{\beta}.\,[s(x,y)]^{\gamma}$$

Where, PSNR is Peak Signal to Noise Ratio, MSE is Mean Square Error, MAE is Mean Approximate Error, IEF is Image Enhancement Factor. SSIM is Structural Similarity Index.

I(x, y) is original input image of size $M\times N$, $I_1(x, y)$ is the reconstructed image, $\eta(x, y)$ is a noisy and blurry image. *l(x, y)* is a Luminance term, *c(x, y)* is a Contrast term and *s(x, y)* is Structural term. The value is in between 0 to 1. If the value is near to 1, there is more structural similarity.

7. EXPERIMENTAL RESULTS

(a) (b) (c)

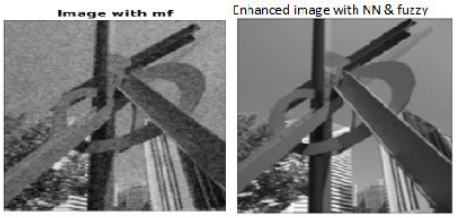


Figure 18: Image (e) is the enhanced image using proposed Fuzzy Membership Function with Deep Neural Network

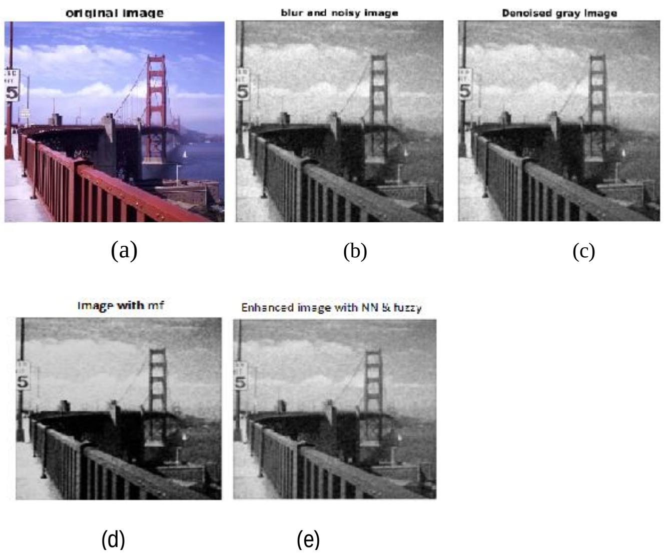


Figure 19: Image (e) is the enhanced image using proposed Fuzzy Membership Function with Deep Neural Network

Table 7: PSNR results of existing approaches with Proposed Fuzzy Membership Function and Proposed Fuzzy with Neural Network for images of various sizes

Image Size	200x281	300x314	300x309	162x310	200x282
Fuzzy with Morphology [13]	16.5811	17.1889	14.2006	16.7532	14.8994
Fuzzy Logic [11]	15.9138	17.8394	14.4746	17.0968	15.7399
Proposed Fuzzy Membership Function	17.5646	19.5063	15.5115	19.074	17.3668
Proposed Fuzzy with Neural Network	18.0151	19.923	15.7777	19.7552	17.8419

PSNR values in the above Table 7 are larger in the proposed Fuzzy Membership Function as well as the proposed Fuzzy with Neural Network.

Table 8: MSE results of existing approaches with Proposed Fuzzy Membership Function and Proposed Fuzzy with Neural Network for images of various sizes

Image Size	200x281	300x314	300x309	162x310	200x282
Fuzzy with Morphology [13]	0.0445	0.0323	0.0381	0.0309	0.0353
Fuzzy Logic [11]	0.0258	0.0164	0.0357	0.0193	0.0266
Proposed Fuzzy Membership Function	0.0175	0.0112	0.0281	0.0123	0.0183
Proposed Fuzzy with Neural Network	0.0159	0.0102	0.0264	0.0108	0.0165

MSE values in the above Table 8 are smaller in the proposed Fuzzy Membership Function as well as the proposed Fuzzy with Neural Network.

Table 9: SSIM results of existing approaches with Proposed Fuzzy Membership Function and Proposed Fuzzy with Neural Network for images of various sizes

Image Size	200x281	300x314	300x309	162x310	200x282
Fuzzy with Morphology [13]	0.1764	0.2998	0.1971	0.5152	0.1698
Fuzzy Logic [11]	0.185	0.3036	0.1983	0.5312	0.1761
Proposed Fuzzy Membership Function	0.6014	0.654	0.2616	0.6619	0.1986
Proposed Fuzzy with Neural Network	0.604	0.659	0.265	0.667	0.6014

SSIM values in the above Table 9 are larger in the proposed Fuzzy Membership Function as well as the proposed Fuzzy with Neural Network.

Table 10: MAE results of existing approaches with Proposed Fuzzy Membership Function and Proposed Fuzzy with Neural Network for images of various sizes

Image Size	200x281	300x314	300x309	162x310	200x282
Fuzzy with Morphology [13]	0.1429	0.246	0.2057	0.1774	0.1462
Fuzzy Logic [11]	0.1259	0.0958	0.1471	0.1109	0.1296
Proposed Fuzzy Membership Function	0.1101	0.0831	0.1325	0.0965	0.1142
Proposed Fuzzy with Neural Network	0.102	0.078	0.1268	0.0892	0.1053

MAE values in the above Table 10 are smaller in the proposed Fuzzy Membership Function as well as the proposed Fuzzy with Neural Network.

Table 11: IEF results of existing approaches with Proposed Fuzzy Membership Function and Proposed Fuzzy with Neural Network for images of various sizes

Image Size	200x281	300x314	300x309	162x310	200x282
Fuzzy with Morphology [13]	0.8197	0.8289	0.8381	0.8024	0.8178
Fuzzy Logic [11]	1.1041	1.3953	1.0943	1.17	1.0732
Proposed Fuzzy Membership Function	1.1787	1.4275	1.1001	1.228	1.1383
Proposed Fuzzy with Neural Network	1.1852	1.4438	1.1199	1.2362	1.1495

IEF values in the above Table 11 are larger in the proposed Fuzzy Membership Function as well as the proposed Fuzzy with Neural Network.

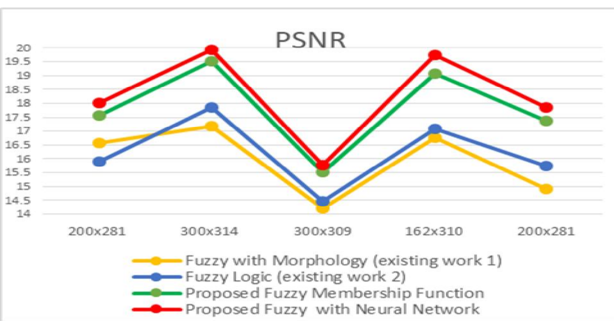


Figure 20: PSNR results for Table 7

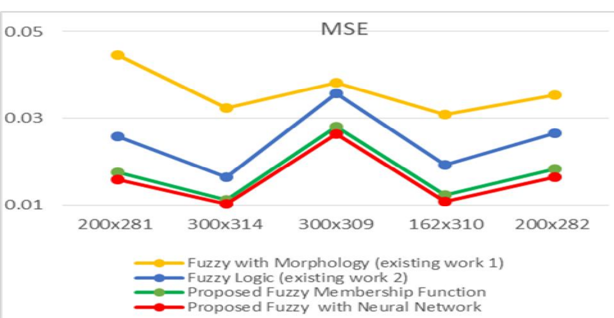


Figure 21: MSE results for Table 8

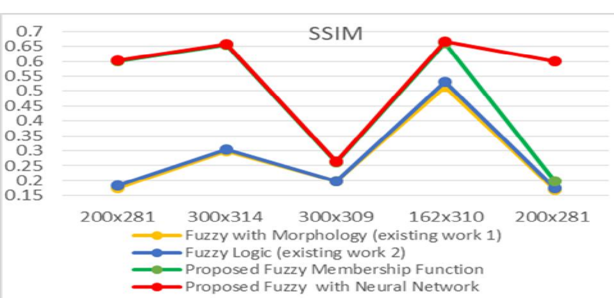


Figure 22: SSIM results for Table 9

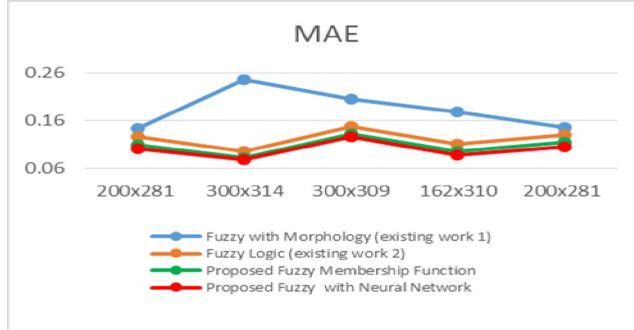


Figure 23: MAE results for Table 10

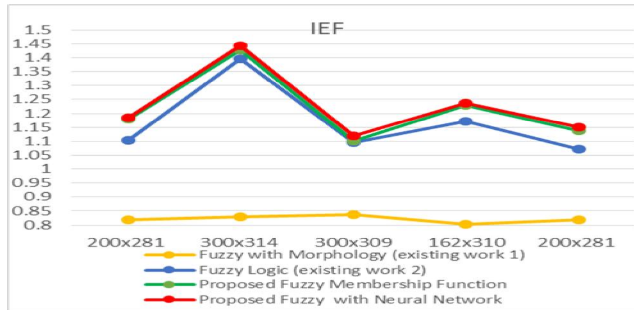


Figure 24: IEF results for Table 11

The experimental values in Table 7, 8, 9, 10, 11 and results in the Figures 20, 21, 22, 23, 24, show that this extension of work of the proposed Fuzzy with Neural Network gives better image quality as compared to Proposed Fuzzy Membership Function as well as to existing work in [11], [12] & [13].

8. CONCLUSION

The proposed work computes focus measures of the defocused images. Based on the principle that defocused images have smaller focus values and focused images have greater focus values, the proposed algorithms of Discrete Wavelet Transform with Gaussian Derivatives (DWTGDR) and Discrete Wavelet Transform with Spatial Frequency (DWTSF) at decomposition level 4, show proper behaviours with decreasing focus measures in 5 iterations.

As the noise and blur amount increased in the each iteration, the proposed algorithm computes decreasing focus measures as compared to existing work.

The scope is further extended to enhance the noisy and blurry images using proposed Fuzzy Membership Function. Images of various sizes and variations in contrast are considered as input images. Fuzzy Membership Function and different fuzzy rules are applied on them which is a knowledge based system. Triangular Membership Function is employed to enhance defocused images from pixel domain or pixel plane to fuzzy domain or plane and the fuzzy rules are applied. The experimental results show that the image is enhanced in greater sense as compared to existing work. This proposed work is further extended with the combination of Neural Network with proposed fuzzy membership function. A set of noisy images are trained by proposed Deep Neural Network for denoising.

Further, the denoised images are converted into fuzzy domain using proposed fuzzy Membership Function and fuzzy rules are applied. The results show that this extension of work of proposed neural Network with Fuzzy also gives better image quality as compared to only proposed Fuzzy Membership Function as well as to existing work.

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