A Denoising of Images in Frequency Domain Using Optimized Neuro Hybrid Fuzzy Filter

M. Sindhana Devi, M. Soranamageswari

Abstract--- ***In image processing domain, the image is corrupted by several types of noises especially when the final product is used for edge detection, image segmentation and data compression. So image de-noising has become a very essential exercise all through diagnose. In the gray scale image the impulse noise can be removed by using the neuro fuzzy (NF) network based impulse noise filtering approach. The each NF filtering approach is a first order sugeno type fuzzy inference system. Since the Sugeno type is not intuitive technique and it also less accurate. In order to improve the accuracy of the NF filtering approach, utilized the hybrid technique of Mamdani and Sugeno based fuzzy interference system approach and an optimized intelligent water drop technique (IWD) in the spatial domain. However the hybridized Sugeno-Mamdani based fuzzy interference system implemented in the spatial domain this leads to reduce the accuracy of the removal of noise. Also the IWD has the issues in selection domination and in ability to handle indistinguishable fitness. In order to overcome these issues in this paper proposed a denoising of images in frequency domain using optimized neuro hybrid fuzzy filter. The optimised Fuzzy intelligence noise filters approach the pixels in the image are converted into frequency domain by using discrete Fourier transform. The noise present in the pixels is filtered by using fuzzy intelligence noise filter. The modified intelligent water drop algorithm applied for frequency domain. After that by using inverse discrete Fourier transform frequency domain pixels of images are converted to original image. In that optimised method noise present in the images are fully eliminated. The performance of the proposed approach evaluated in terms of Mean Squared Error (MSE) and Peak Signal–to–noise Ratio (PSNR), Structural Similarity (SSIM), Mean Absolute Error (MAE) and Maximum Difference value (MD).***

Keywords--- ***Fuzzy inference system, Neuro Fuzzy system, Sugeno type, intelligent water drop algorithm.***

I. INTRODUCTION

Digital image may be infected through impulse noise during photo acquisition or transmission. Two common varieties of impulse noise [1] are the salt-and-pepper noise and the random valued noise. For image corrupted by means of salt-and-pepper noise (respectively, random-valued noise), the noisy pixels can take most effective the maximum and the minimal values (respectively, any random value) in the dynamic range. Consequently, it may critically degrade the image quality and cause some loss of information. Several methods were proposed for the recuperation of image corrupted through impulse noise, and it's far widely recognized that linear filters should produce severe image blurring even in low noise density.

Consequently, nonlinear filters have been widely exploited due to their much improved filtering performance in terms of impulse noise attenuation. Various filtering algorithms have been proposed. Among them, the family of median filters is the most popular and holds a dominant position in this area for its outstanding noise suppression ability. The most representative paradigm in this family is known as "Switching Median Filtering" (SMF) [2] , which partitions the whole filtering process into two sequential steps—noise detection and filtering. By utilizing the a priori knowledge obtained from the noise detection step, the filtering step could be more targeted and does not need to touch those uncorrupted pixels. Obviously the accuracy of the noise detection is critical to the final result.

A Neuro-fuzzy system [3] based on a fuzzy technique which is trained by a learning algorithm derived from neural network theory was implemented for the removal of noise. A Neuro – fuzzy network for noise filtering in gray scale images that combines two Neuro fuzzy (NF) filters with a post processor to produce the output.

However Sugeno type [4] is not intuitive technique and it also less accurate. In order to overcome these problems Hybrid Neuro-Fuzzy Filter [5] with Optimized Intelligent Water drop Technique [6] is introduced where hybridized Sugeno-Mamdani based fuzzy interference system is implemented in both the NF filters to obtain more efficient noise removal system. The Hybrid method maintains the accuracy of the Sugeno model and also the interpretable capability of the Mamdani model.

Since the hybridized Sugeno-Mamdani based fuzzy interference system implemented in the spatial domain this leads to reduce the accuracy of the removal of noise. In order to improve the accuracy of the removal of noise in this paper proposed a denoising of images in frequency domain using optimized neuro hybrid fuzzy filter.

II. LITERATURE SURVEY

Fuzzy inference system (FIS) (Haji, M., et.al.2012) proposed [7] in the initialization step of the optimization process from the handwritten images to increase the convergence time of the noise removal and recognition in the system. The FIS is used to improve the initial guesses for latent variables. In this research the unsupervised learning approach utilized to overcome the noise pattern issues. The performance of the proposed Fuzzy inference system methods evaluated in terms of recognition rate and speed. However this approach has the higher computational complexity.

Manuscript received February 01, 2019

M. Sindhana Devi, Research Scholar, Department of Computer Science and Research Development, Government Arts College, Coimbatore, Tamil Nadu, India. (e-mail: sindhana27@gmail.com)

Dr.M. Soranamageswari, Assistant Professor, Department of Computer Science and Research Development, Government Arts College, Coimbatore, Tamil Nadu, India. (e-mail: drswarnakannapan@gmail.com)

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

Hybrid method (Sadeghi, S., et.al.2012) proposed [8] based on cellular automata (CA) and fuzzy cellular Automata (FCA) to eliminate the impulse noises from noisy images. The proposed Hybrid method has two steps. In the first step depends on the statistical information the noisy pixels are detected by the CA, after that using this information the noisy pixel modify by the FCA. The proposed method performs well in the gray scale test images and performs better than the traditional approaches. However the cellular automata require the large computational resources.

Novel two stage noise adaptive fuzzy switching median (NAFSM) filter (Toh, K. K. V., & Isa, N. A. M. 2010) presented [9] for salt and pepper noise detection and removal. Initially the detection stage utilizes the histogram of the corrupted image to predict the noise pixels. Then these detected noise pixels are subjected to the second stage of the filtering action while the noise free pixels are engaged and remains are unprocessed. The NAFSM filter is the hybrid between the simple adaptive median filter and fuzzy switching median filter. The adaptive behavior enables the NAFSM filter to enhance the size of the filtering window based on the density of noise make it possible to filter high density of salt and pepper noise.

Novel approach (LatifoğLu, F. 2013) presented [10] to speckle noise filtering based on Artificial Bee Colony (ABC) algorithm. The aim of the proposed approach is a speckle noise denoising using the 2D FIR filter which is optimized by ABC algorithm. Initially the speckle noises with variances are added to the synthetic test images. After that the noisy images are denoised by using the proposed filter and other filters such as Gaussian, mean and average filters. The result shows that the proposed filter is efficiently detect the general coefficient of the filter such as signal to noise ratio, peak signal noise ratio, mean square error. However the proposed speckle noise filtering makes the interpretation more difficult which degraded the quality of image.

Novel Adaptive iterative fuzzy filter (Ahmed, F., & Das, S. 2014) proposed [11] for denoising images corrupted by the impulse noise. The proposed filter has two stages. In first stage the adaptive fuzzy filter utilized detecting the noisy pixels. In the second stage, the denoising is performed on the noisy pixels by performing the weighted mean filtering operation on the neighbourhood uncorrupted pixels. The result shows that the proposed filters perform well compare to traditional filters.

A New Edge detection technique (Verma, O. P., et.al.2013) proposed [12] to solve the noisy image using fuzzy derivative and bacterial foraging optimization algorithm. The main aim of this research is a detection of edges in the presence of noise using the bacterial foraging (BF) with reduced computational complexity. The new fuzzy inference rules are devised and the direction of movement of the each bacterium is predicted using these rules. During the foraging suppose the bacterium encounters the noisy pixel it first remove the noisy pixel by using the adaptive fuzzy switching median filter. The proposed new edge detector performs better than the traditional edge detector such as Sobel, Canny, ACO and GA.

Development of adaptive fuzzy based image filtering techniques (Agrawal, A., et.al.2011) presented [13] for the efficient noise reduction in medical images. The proposed system present the new technique for filtering narrow tailed and medium narrow tailed noise by a fuzzy filter. First, the system estimates the fuzzy derivative to the less sensitive to local variations due to image structure like edges. Second, the membership functions are adapted accordingly to the noise level to perform the fuzzy smoothing. The proposed filter has two stages. In the first stage is to computes the fuzzy derivative for eight various directions. In the second stage is utilising the fuzzy derivatives to perform fuzzy smoothing by weighting the contributions of neigh boring pixel values. The both two stage are based on the fuzzy rules which utilise the membership functions. After that the filter can applied to reduce the heavy noise. Then the shape of the membership functions is adapted according to the remaining noise level by using the distributions of the homogeneity in the image.

Image filtering technique (Hussain, A., et.al.2012) proposed [14] based on fuzzy logic control to eliminate impulse noise for both low and highly corrupted images. The proposed filtering technique based on noise detection, noise removal and edge preservation modules. This technique combines histogram estimation and fuzzy number construction process to increase the detection rate. It has two separate modules for the noise removal and the detail of the image can be preserved in the restored image. Then the sensitivity analysis performed to test the goodness of the image preservation capability of the proposed Image filtering technique. The result shows that the proposed approach is perform better than the traditional filtering approaches. However, the Image filtering technique does not preserve the detail of image.

Novel fuzzy system based method (SOYTÜRK, M. A., et.al.2014) proposed [15] for speckle noise removal. The proposed system builds with the fuzzy inference system, edge detection, and dilation unit, and an image combiner. The fuzzy inference system contains the 5 inputs and 1 output and then filtering the speckle noisy image. The input with the fuzzy system consists of the center pixel of the filtering window and it contains the 2 horizontal and vertical neighbors. The result shows that the proposed filtering approach reduces the speckle noise from the digital images while preserving edges, textures and necessary details.

New efficient fuzzy based decision algorithm (FBDA) (Nair, M. S., & Raju, G. 2012) proposed [16] for the restoration of images in corrupted with high density of impulse noises. The FBDA is the fuzzy based switching median filter in which the filtering is applied to only the corrupted pixels in the image during the uncorrupted pixels are remains in changed. The proposed FBDA algorithm computes the difference measure for each pixel based on the corrupted pixel in the selected window then calculated the membership value for each pixel depends on highest difference.

Then finally the median filter is applied to remaining

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

pixels in the window to get the restored values for the position of the current pixels.

III. PROPOSED METHODOLOGY

In this paper the hybridized Sugeno-Mamdani based fuzzy interference system methodology the pixel in the image are convert in to the frequency domain by using discrete Fourier transform. After that the noise patterns in the pixels are filtered by utilize fuzzy intelligence noise filter. The modified intelligent water drop algorithm applied for frequency domain to parameter and membership tuning. After that apply the inverse discrete Fourier transform in frequency domain pixels of images which are used convert in to original image. The proposed methodology apply in the

3.1 Structure of the Neuro Hybrid-Fuzzy Filter

The fuzzy system is basically classified in to two families like Mamdani and Sugeno, based on the fuzzy rules. Each filter is a combination of the first order Sugeno and Mamdani fuzzy interference system.

The Mamdani model is denoted by the inputs as x_1, x_2, x_3, x_4 and the output is denoted as y. Each input has three membership functions and the output has linear membership function. The model is represented as

Rule k: if x_1 is R_1^k; x2 is R_2^k; x_3 is R_3^k and x_4 is R_4^k (1)

Then Y is S_k, where R and S are the fuzzy sets for the input x and output y respectively. The output Y is represented as

$$y_i = \frac{\sum_{k=0}^{K} a_k v_k s_k}{\sum_{k=0}^{K} a_k v_k} \qquad (2)$$

Where a_k is the degree, the input x matches the rule computed and v_k is volume of the output fuzzy set and s_k is the centroid of the output fuzzy set S_k.

The Sugeno model systems utilize the rule structure that has fuzzy antecedent and consequent parts. The model is represented as

Rule k: if x_1 is R_1^k; x2 is R_2^k; x_3 is R_3^k and x_4 is R_4^k (3)

Then Y is $b_k(X)$. Where $b_k(X) = c_k = c_{k0} + c_{k1}x_1 + c_{k2}x_2 + \ldots + c_{kn}x_n$ (4)

c_{k1} is the consequent parameter. Thus for any input x, output y is evaluated by centroid defuzzification

$$Y_i = \frac{\sum_{k=1}^{K} a_k \, b_k(X)}{\sum_{k=0}^{K} a_k} \qquad (5)$$

The number of inputs is 4, 3 membership functions, and number of output is 1, thus the number of rules is given by 3^4 that is k =81.

Both the Mamdani and Sugeno models are expressed in a compact form,

Rule k: if x_1 is R_1^k; x2 is R_2^k; x_3 is R_3^k and x_4 is R_4^k (6)

Then Y is D_k.

Where D_k can be either S_k for the Mamdani model, or b_k for the Sugeno model. R_i^k denotes the membership function of the i th input of the kth rule. The input membership functions are generalized bell type that is defined as,

$$R_i^k(x_i) = \frac{1}{1 + \left|\frac{x_i - t_{ik}}{u_{ik}}\right|^{2d_{ik}}} \qquad (7)$$

Where x_i is the ith input, t_{ik}, u_{ik} *and* d_{ik} are the antecedent parameters. The output of the Y of each NF filter is the weighted average of the individual rule outputs. The weighting factor w_k of the each rule is the multiplication of four input membership values. The weighting factors w_1 to w_{81} and the output Y of each NF filter is calculated by

$$w_k = R_1^1(x_1) \text{ X } R_2^1(x_2) \text{ X } R_3^1(x_3) \text{ X } R_4^1(x_4)$$
$$w_2 = R_1^1(x_1) \text{ X } R_2^1(x_2) \text{ X } R_3^1(x_3) \text{ X } R_4^2(x_4)$$
$$\vdots$$
$$w_{81} = R_3^1(x_1) \text{ X } R_2^3(x_2) \text{ X } R_3^3(x_3) \text{ X } R_4^3(x_4) \qquad (8)$$

3.1.1 Hybrid Model

The overall output Y for Sugeno model is determined by eqn (5), and that of the Mamdani model is determined by (2). In Mamdani model, the conditions of volumes $v_1 = v_2 = \ldots = v_k$, having same size of the output membership functions, where as in Sugeno model when it is zero order, both the output functions become similar. Therefore the general form of the output function is given by,

$$Y = \sum_{k=1}^{K} \frac{a_k v_k}{\sum_{k=1}^{K} a_k} \, b_k(X) \quad (9)$$

Eqn 10 is the generalized fuzzy interference model that hybridized both Sugeno model and Mamdani model. Therefore the hybridized model is defined as,

Rule k: if x_1 is R_1^k; x2 is R_2^k; x_3 is R_3^k and x_4 is R_4^k (10)

Then Y is $S_{k1}(v_k, b_{k1}(X))$.

Thus the output of both the hybridized NF filter is calculated using this equation. The essential effectiveness of (11), can not only preserve the interpretable capability of the Mamdani model but also maintain the accuracy of the Sugeno model. The output of the hybrid NF filter is truncated to the 8 bit integer values Y_p'

Thus the final output of the proposed filter Y_F is calculated by the average of the output of the two hybrid NF filters. The function round (), rounds the element x to nearest integer.

$$Y_F = \text{round}\left(\frac{1}{2} \sum_{p=1}^{2} Y_p'\right) \qquad (11)$$

This output is then fed to the post processor to generate the output of the final filter. The internal parameters of the hybridized NF filters are optimized using hybrid learning rule to reduce the error. The antecedent and the consequent parameters are optimized using gradient descendent and least mean squares algorithm respectively.

3.2 Discrete Fourier Transform

In the proposed optimised Fuzzy intelligence noise filter approach the pixels in the image are converted into frequency domain by using discrete Fourier transform. The impulse noise removal cannot be successfully implemented in the spatial domain. Rather it's performed in the frequency domain by using discrete Fourier transform.

The discrete Fourier transform can be denoted by the following equation.

Let $v_i, j \in [0, \ldots\ldots\ldots N-1]$ (12)

Be the sampled version of the images, v(t) where the N is the number of samples.

The Fourier transform of v (t) is given by

$$V(t) = F[v(t)] = \int_{-\infty}^{\infty} v(t) e^{-2\pi i f t} dt \quad (13)$$

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

The v(f) can only exists if the v(t) is absolutely integrable, i.e,

$\int_{-\infty}^{\infty} |v(t)|\, dt < +\infty$

In this case, the v (t) is integrable if and only if |v(t)| is integrable, so the terms "absolutely integrable" and "integrable" amount to the same thing.

In order to compute (13) for the sequence of N complex number $X_0, X_1, X_2, \dots \dots \dots . X_{N-1}$

$$V_k = \frac{1}{N}\sum_{j=0}^{N-1} e^{\frac{-2\pi ijk}{N}} V_j \qquad (14)$$

Using Euler's Equation

$$e^{i\theta} = cos\theta + isin\theta \qquad (14a)$$

In the kernel of the transform in (14) to be written as

$$e^{\frac{-2\pi ijk}{N}} = \cos\left(\frac{-2\pi jk}{N}\right) + isin\left(\frac{-2\pi jk}{N}\right) \quad (14b)$$

An even function is one that has the property that f(-x)=f(x). An odd function has the property that f(-x)=-f(x). Using this definition, sin (-θ) =-sinθ, is an odd function and since cos (-θ) =cos θ, cosine in an even function. Using the odd even function properties of sine and cosine the equation (4b) rewrite as

$$e^{\frac{-2\pi ijk}{N}} = cos\left(\frac{2\pi jk}{N}\right) - isin\left(\frac{2\pi jk}{N}\right) \quad (14c)$$

Then substituting the Equation (4c) in to (4) then obtain

$$V_k = \frac{1}{N}\sum_{j=0}^{N-1}\left(cos\left(\frac{2\pi jk}{N}\right) - isin\left(\frac{2\pi jk}{N}\right)\right) v_j \quad (15)$$

3.3 Modified Intelligent Water Drops Algorithm (IWD) based optimization of Membership values for the Inputs

The membership values are assigned to the inputs for optimization to further improve the accuracy of the system as it decides the efficiency of the noise removal in the images. Thus the process known as intelligent Water Drop technique (IWD) is implemented in the early work. The drop is considered as Membership value. The parameters that define the efficiency of the drop are soil, velocity and distance. For an efficient water drop, soil content must be low; velocity should be high as both are inversely proportional. Here the main parameter is the error function that should be low for the membership function. However the IWD has the some limitations such as selection domination and inability to handle indistinguishable fitness. So in this paper the Modified Intelligent Water Drop (IWD) technique proposed which contains two ranking based selection methods two overcome the limitations of the IWD. The two ranking based selection methods are Multi objective ranking and Roulette wheel selection methods.

3.3.1 Ranking Selection

The ranking selection methods are based on the rationale fitness rank rather than the fitness value of the soil to predict the probability of the each pixel in removing the noise in the images. To select the each pixel to be included in the path, firstly all possible pixels are ranked based on the soil values. The pixel with the higher rank is assigned as the higher rank. All ranks are then mapped to the selection probability by mapping function. The Performance of the selection method depends on both the mapping function and the selection pressure (SP) parameter. The parameter SP refer to the tendency of chosen the best pixel. Based on the mapping function utilize the ranking selection methods can be classified in to two categories like Multi objective ranking and Roulette wheel selection methods. The probability of the selection is predicts in advance and it remains the same throughput the search process.

3.3.2. Multi Objective Ranking

The multi objective ranking is defined as where proportional and rank-based fitness assignment is troubled it is consider that individuals display only one objective functions value. In the many real world problems, however, there are several criteria which have to be considered in order to evaluate the quality of an individual. Only focus on the basis of the comparison of the several criteria like multi objective can a decision is made as the superiority of one individual over another. Then as in the single objective problems, an order of individual within the populations can be established from the reciprocal comparisons multi objective ranking. After this order can be established the single-objective ranking methods from the subsection can be used to convert the order of the individuals to corresponding fitness values.

3.3.3 Roulette wheel selection

The roulette-wheel selection is the simplest selection scheme which is refers in the stochastic sampling with replacement. This is a stochastic algorithm and contains the following technique:

The individual are mapped in to the contiguous segments of the line, such that each segment is equal in size to its fitness. A random number is generated and the individual segments span the random number selection. The iterative process is repeated until the desired number of individuals is obtained (called mating population). This technique is analogous to a roulette wheel with each slice proportional in size to the fitness.

Algorithm for optimal membership value Selection using Modified IWD

Input: Initial Membership values for pixels

Output: Optimized value of Membership

1. Formulate the optimization problem as a graph that is fully connected.
2. Assign initial values of membership to the pixels in the image.
3. Let number of membership values be m;
4. Apply the modified IWD to construct the complete solution
5. Multi objective ranking and roulette-wheel selection applies the IWD to construct its solutions.
6. Select best membership value in the values m as M_{best};
7. Update the global best solution
8. End while
9. Return $M_{best.}$

Thus the best membership value to the input values of each pixel improves the efficiency of the noise removal. This optimization adds another improvement in the new proposed methods for impulse noise removal.

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

3.4 Inverse Discrete Fourier Transform

Finally after removing the impulse noise from the image then reconstructed proposed optimised Fuzzy intelligence noise filter approach back to spatial domain to get the original image by using inverse Discrete Fourier Transform.

The inverse Fourier transform written as V (f) by

$$v(t) = F^{-1}[V(f)] = \int_{-\infty}^{\infty} v(f) e^{2\pi i f t} dt \quad (16)$$

In order to compute (6) for the sequence of N complex number of the Equation (12) must perform an inverse discrete time Fourier transform called the IDFT (inverse Discrete Fourier Transform) is given by

$$V_k = \sum_{j=0}^{N-1} e^{\frac{-2\pi i j k}{N}} V_j \quad (17)$$

Then by using the Equation (14)

$$V_k = \frac{1}{N} \sum_{j=0}^{N-1} e^{\frac{-2\pi i j k}{N}} V_j$$

The summation result is multiply by 1/N. this is not the case in the Equation (17). In the some expositions, both (17) and (14) are multiply by $1/\sqrt{N}$, in order to keep the DFT and IDFT symmetric. The neglected such an approach while development because it's both complicates the presentations of the PSD and requires slightly more computation.

Substituting the Euler Equation in the already given Equation (14a).

$$e^{i\theta} = cos\theta + isin\theta$$

In to the Equation (7) the result as

$$v_k = \sum_{j=0}^{N-1} \left[cos\left(\frac{2\pi j k}{N}\right) + isin\left(\frac{2\pi j k}{N}\right) \right] V_j \quad (18)$$

The multiplication of two complex numbers result may be expressed as

$$z_1 z_2 = (x_1 + iy_1)(x_2 + iy_2) = x_1 x_2 - y_1 y_2 + i(x_1 y_2 + y_1 x_2) \quad (18a)$$

Depends on the (8a) conclude that the real part of $z_1 z_2$ is given by

$$real(z_1 z_2) = x_1 x_2 - y_1 y_2 \quad (18b)$$

Then the imaginary part of $z_1 z_2$ is given by

$$imaginary(z_1 z_2) = x_1 y_2 + y_1 x_2 \quad (18c)$$

The real valued image as given in the input, require to compute the result in (18c) substituting the (18b) in to (18) yields,

$$real(v_k) = \sum_{j=0}^{N-1} \left[cos\left(\frac{2\pi j k}{N}\right) real(V_j) - sin\left(\frac{2\pi j k}{N}\right) imaginary(V_j) \right] \quad (19)$$

Computing only the real part of the IDFT saves the 2N multiplies and N addition for each frequency index, k computed in the Equation (19) than in 18. The Comparison of 19 and 15 is the

$$V_k = \frac{1}{N} \sum_{j=0}^{N-1} \left(cos\left(\frac{2\pi j k}{N}\right) - isin\left(\frac{2\pi j k}{N}\right) \right) v_j$$

Show that both take about the same amount of the time to compute. Finally output of the result shows that get the original image without any noise.

IV. RESULT AND DISCUSSION

This section deals with experimental results that demonstrate the performance of the proposed. The proposed Frequency domain Neuro Hybrid Fuzzy Modified IWD (FD-NHF-MIWD) is compared with the existing Neuro Hybrid Fuzzy IWD (NHF-IWD)using the quantitative measures such as Mean Squared Error (MSE) and Peak Signal–to–noise Ratio (PSNR), Structural Similarity (SSIM), Mean Absolute Error (MAE) and Maximum Difference value (MD).

A. Mean Square Error (MSE)

The mean squared error (MSE) or mean squared deviation (MSD) of an estimator measures the average of the squares of the errors or deviations, that is, the difference between the estimator and what is estimated.

$$\mathrm{MSE} = \frac{1}{\mathrm{M} \times \mathrm{N}} \sum_{i=1}^{M} \sum_{j=1}^{N} (\mathrm{O}(i,j) - \mathrm{R}(i,j))^2$$

Where O (i, j) and R (i, j) are pixels of the original and the restored test image with size as M X N.

B. Peak Signal Noise Ration (PSNR)

Peak signal-to-noise ratio (PSNR) is used to represent the index of media quality analysis and substitutes the average MSE of frames or pixels in the PSNR computing equation to obtain the PSNR value of the media segment, expressed as,

$$\mathrm{PSNR} = 20 \log_{10}\left(\frac{255}{\sqrt{\mathrm{MSE}}}\right)$$

C. Mean Absolute Error (MAE)

The mean absolute error (MAE) is a quantity used to measure how difference between the original image and the noise free image. The mean absolute error is given by

$$\mathrm{MAE} = \frac{1}{n} \sum_{i=1}^{n} |\mathrm{O}(i,j) - \mathrm{R}(i,j)|$$

D. Max Difference (MD) Value

The max difference value (MD) is a quantity used to measure how difference between the original image and the noise free restored image. The MD is given by

$$\mathrm{MD} = \max(\mathrm{O}(i,j) - \mathrm{R}(i,j))$$

Table 4.1: Comparison of MSE Values of the Existing and Proposed Filters with Different Noise Density

Filters	5%	10%	15%	20%	25%
Hybrid NF Filter with IWD	15	21	23	29	35
Proposed	10	16	18	24	30

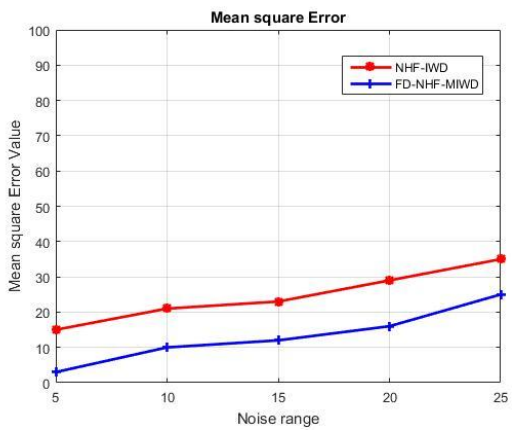

Figure 4.1: Comparison graph for the MSE Values of the Existing and Proposed Filters with different Noise Density

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

The Comparison of MSE Values of the Existing and Proposed Filters with Different Noise Density is performed.

From table 4.1, it is inferred that the proposed Frequency domain Neuro Hybrid Fuzzy Modified IWD (FD-NHF-MIWD) stands out in its performance when compared with the existing Neuro Hybrid Fuzzy IWD (NHF-IWD).

Table 4.2: Comparison of PSNR Values of the Existing and Proposed Filters with Different Noise Density

Filters	5%	10%	15%	20%	25%
Hybrid NF Filter with IWD	56	54.3	51.05	45.93	43
Proposed	51	50	47.32	41.89	39

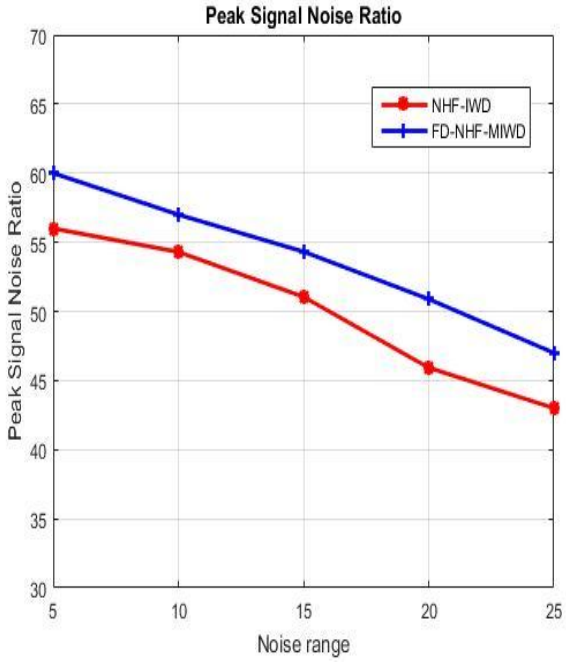

Figure 4.2: Comparison graph for the PSNR Values of the Existing and Proposed Filters with different Noise Density

The Comparison of PSNR Values of the Existing and Proposed Filters with Different Noise Density is performed. From table 4.2, it is inferred that the proposed Frequency domain Neuro Hybrid Fuzzy Modified IWD (FD-NHF-MIWD) stands out in its performance when compared with the existing Neuro Hybrid Fuzzy IWD (NHF-IWD).

Table 4.3: Comparison of MAE Values of the Existing and Proposed Filters with Different Noise Density

Filters	5%	10%	15%	20%	25%
Hybrid NF Filter with IWD	27	28.2	28.9	29.4	30.1
Proposed	20.8	22.5	24	26	28.6

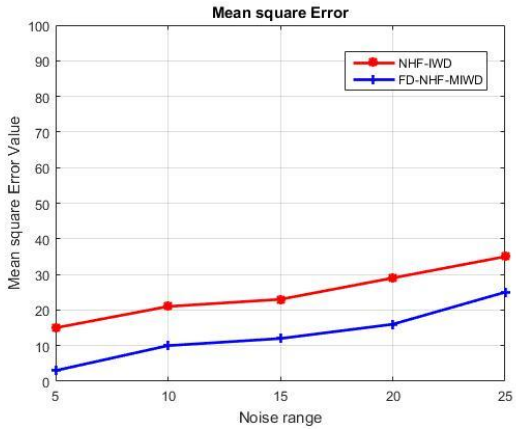

Figure 4.3: Comparison graph for the MAE Values of the Existing and Proposed Filters with different Noise Density

The Comparison of PSNR Values of the Existing and Proposed Filters with Different Noise Density is performed. From table 4.3, it is inferred that the proposed Frequency domain Neuro Hybrid Fuzzy Modified IWD (FD-NHF-MIWD) stands out in its performance when compared with the existing Neuro Hybrid Fuzzy IWD (NHF-IWD).

Table 4.4: Comparison of MD Values of the Existing and Proposed Filters with Different Noise Density

Filters	5%	10%	15%	20%	25%
Hybrid NF Filter with IWD	211	211.60	211.90	212.40	212.90
Proposed	200	209.50	210	210.50	211

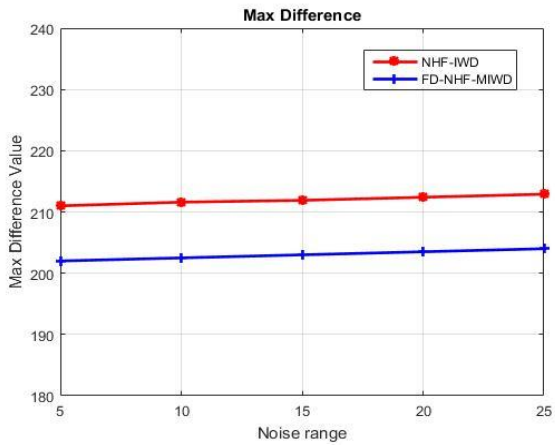

Figure 4.4: Comparison graph for the MD Values of the Existing and Proposed Filters with different Noise Density

The Comparison of MD Values of the Existing and Proposed Filters with Different Noise Density is performed.

The Comparison of PSNR Values of the Existing and Proposed Filters with Different Noise Density is performed. From table 4.4, it is inferred that the proposed Frequency domain Neuro Hybrid Fuzzy Modified IWD (FD-NHF-MIWD) stands out in its performance when compared with the existing Neuro Hybrid Fuzzy IWD (NHF-IWD).

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

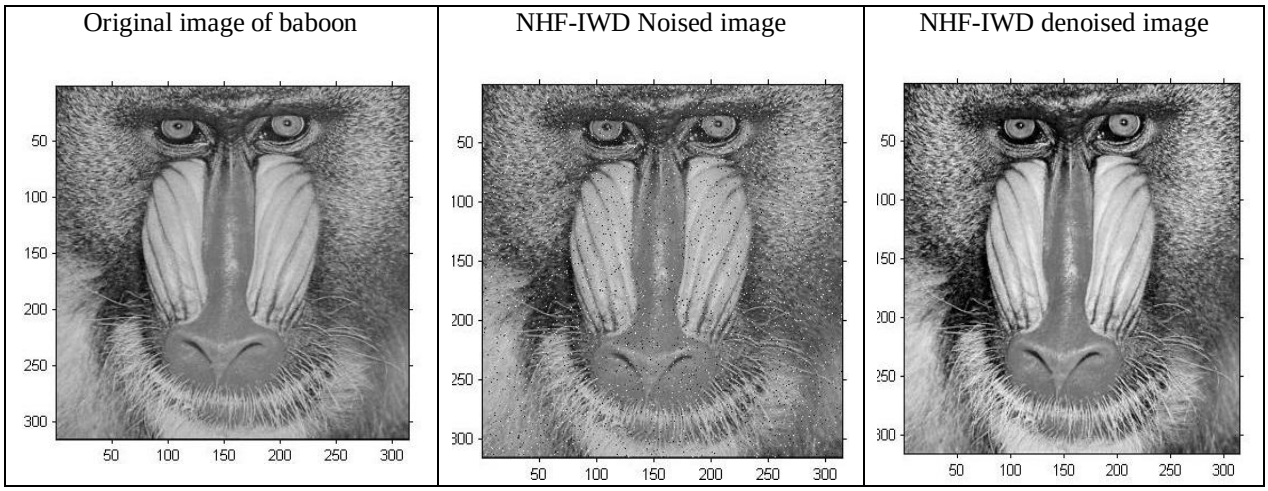

Figure 1 a) Original image of baboon 1 b) NHF-IWD Noised image 1 c) NHF-IWD denoised image

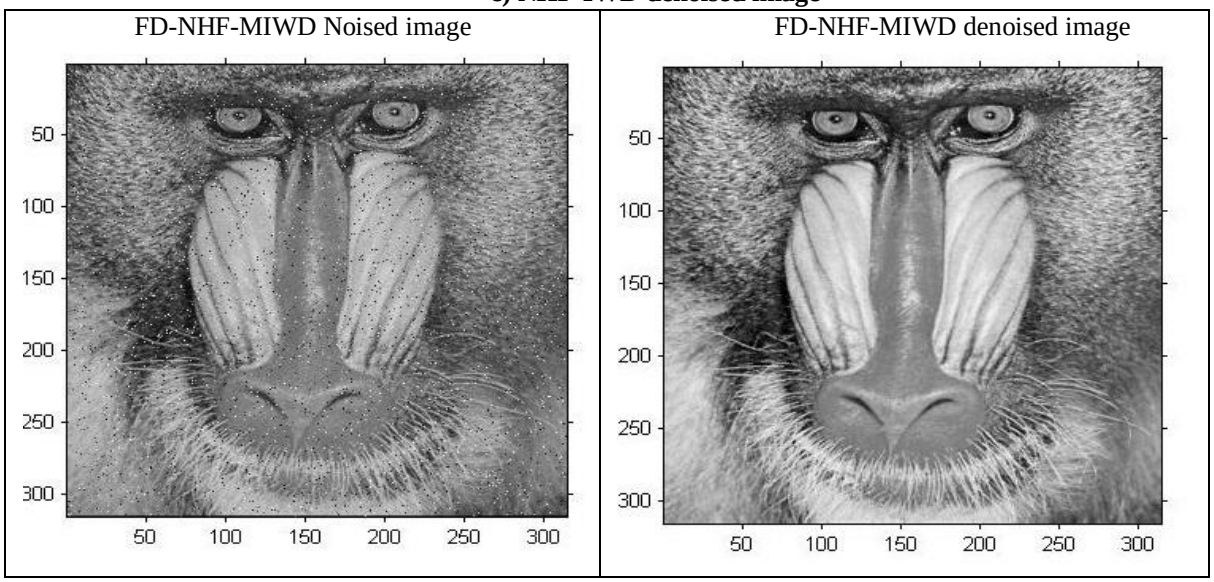

Figure 2a) FD-NHF-MIWD Noised image 2b) FD-NHF-MIWD denoised image

V. CONCLUSION

In this paper proposed a denoising of images in frequency domain using optimized neuro hybrid fuzzy filter. The optimised Fuzzy intelligence noise filters approach the pixels in the image are converted into frequency domain by using discrete Fourier transform. The fuzzy intelligence noise filter utilized to remove the noise in the pixels. Then the modified intelligent water drop (IWD) algorithm applied to parameter and membership tuning in the frequency domain. Finally the inverse discrete Fourier transform frequency applied to convert in to the original image. The performance of the proposed approach tested with Mean Squared Error (MSE) and Peak Signal–to–noise Ratio (PSNR), Structural Similarity (SSIM), Mean Absolute Error (MAE) and Maximum Difference value (MD). The experimental results also proved that the proposed filter effectively removes the impulse noise from the gray scale images. The proposed method is more efficient than the existing filtering methods in the noise removal and its performing better in the practical applications.

REFERENCES

1. Lu, C. T., & Chou, T. C. (2012). Denoising of salt-and-pepper noise corrupted image using modified directional-weighted-median filter. Pattern Recognition Letters, 33(10), 1287-1295.
2. Duan, F., & Zhang, Y. J. (2010). A highly effective impulse noise detection algorithm for switching median filters. IEEE Signal Processing Letters, 17(7), 647-650.
3. Li, Y., Sun, J., & Luo, H. (2014). A neuro-fuzzy network based impulse noise filtering for gray scale images. Neurocomputing, 127, 190-199.
4. Sindhana Devi, M., & Soranamageswari, M. (2017, July). A sugeno and tsukamoto fuzzy inference system for denoising medical images, International journal of Recent Scientific Research, 8(7), (pp.18074-18078).
5. Sindhana Devi, M., & Soranamageswari, M. (2016, March). A Hybrid technique of Mamdani and Sugeno based fuzzy interference system approach. In Data Mining and Advanced Computing (SAPIENCE), International Conference on (pp. 340-342). IEEE.

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

6. Alijla, B. O., Wong, L. P., Lim, C. P., Khader, A. T., & Al-Betar, M. A. (2014). A modified intelligent water drops algorithm and its application to optimization problems. Expert Systems with Applications, 41(15), 6555-6569.
7. Haji, M., Bui, T. D., & Suen, C. Y. (2012). Removal of noise patterns in handwritten images using expectation maximization and fuzzy inference systems. Pattern Recognition, 45(12), 4237-4249.
8. Sadeghi, S., Rezvanian, A., & Kamrani, E. (2012). An efficient method for impulse noise reduction from images using fuzzy cellular automata. AEU-International Journal of Electronics and Communications, 66(9), 772-779.
9. Toh, K. K. V., & Isa, N. A. M. (2010). Noise adaptive fuzzy switching median filter for salt-and-pepper noise reduction. IEEE signal processing letters, 17(3), 281-284.
10. LatifoğLu, F. (2013). A novel approach to speckle noise filtering based on artificial bee colony algorithm: an ultrasound image application. Computer methods and programs in biomedicine, 111(3), 561-569.
11. Ahmed, F., & Das, S. (2014). Removal of high-density salt-and-pepper noise in images with an iterative adaptive fuzzy filter using alpha-trimmed mean. IEEE Transactions on fuzzy systems, 22(5), 1352-1358.
12. Verma, O. P., Hanmandlu, M., Sultania, A. K., & Parihar, A. S. (2013). A novel fuzzy system for edge detection in noisy image using bacterial foraging. Multidimensional Systems and Signal Processing, 24(1), 181-198.
13. Agrawal, A., Choubey, A., & Nagwanshi, K. K. (2011). Development of adaptive fuzzy based Image Filtering techniques for efficient Noise Reduction in Medical Images. IJCSIT) International Journal of Computer Science and Information Technologies, 2(4), 1457-1461.
14. Hussain, A., Bhatti, S. M., & Jaffar, M. A. (2012). Fuzzy based impulse noise reduction method. Multimedia Tools and Applications, 60(3), 551-571.
15. SOYTÜRK, M. A., BAŞTÜRK, A., & YÜKSEL, M. E. (2014). A novel fuzzy filter for speckle noise removal. Turkish Journal of Electrical Engineering & Computer Sciences, 22(5), 1367-1381.
16. Nair, M. S., & Raju, G. (2012). A new fuzzy-based decision algorithm for high-density impulse noise removal. Signal, Image and Video Processing, 6(4), 579-595.

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication