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A Fuzzy Based IMAGE Denoising Filter Using Non-Linear Fuzzy Membership Functions

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Abstract – Quality of images are often degraded by the presence of noise which obscures different image features. The process of restoring original quality images from noisy nature is often an unavoidable and challenging step in image enhancement. Gaussian noise is one of the most commonly occurring noise distributions which is mainly occurred during acquisition and transmission of images. Even though averaging filter is widely used to remove Gaussian noise, it causes significant blurring of edges in the filtered image. In this paper, a method of improving the denoising capability of a basic averaging filter using fuzzy logic is discussed and further, a new non-linear fuzzy membership function (FMF) is proposed to improve the noise filtering as well as edge retention capability of the existing filter. The experimental results justify the improved quality of denoising of the proposed filter.

Index Terms – Image Denoising, Gaussian Noise, Fuzzy Logic, Fuzzy Membership Function (FMF).

1. INTRODUCTION

Image noises are unwanted signals that cause random variation in pixel intensities within the image. It usually manifests itself as random speckles on a smooth surface and it can obscure details within the image. The most generic noise model is additive noise, where the observed image I' can modeled as the sum I' = I + N, where N is the 2D noise signal that corrupts the original image I. Noise signals N can be of different distribution types [2] and the most commonly occurring one is Gaussian noise where the noise signal closely follows a Normal distribution with a specific mean and standard deviation. Image denoising is the process of removing noise from an image to retain the characteristics of the original image I. It is applied in many situations were noise may be introduced in images mainly during image generation, transmission or processing [3]. The basic requirements of any denoising technique include proper noise filtering and preservation of edges within the image [4]-[5]. Many algorithms are available for denoising, some of them are very complex and computationally expensive, while few others are simple and lightweight. Selecting the appropriate filter depends on the context where it is used.

The Averaging filter is a widely used noise filter in image processing, especially in the context of removing Gaussian noises. Here, images are 'smoothed' by reducing the magnitude of intensity differences between neighboring pixels. For each pixel in the image, the intensity value is corrected based on the average of pixel intensity differences in all directions. Although the filter is fast and light weight, the major drawback of the averaging filter is that there is no mechanism to determine whether a measured difference in pixel intensity in a particular direction is due to noises or an edge and therefore, causes blurring of edges in the filtered image. Edges are being focused as they are a local variation and the algorithm needs to handle such structures differently while smoothing. The primary motivation behind introducing ideas in fuzzy logic [1] is to be able to make this distinction between regions of noises and edges to a great extent and thus, making the filter less sensitive to the latter.

2. RELATED WORKS

The core idea of fuzzy-based filter is the estimation of fuzzy directives [7-15] which plays a vital role for taking various decisions regarding the filtering process. Several fuzzy based noise filters have been developed for the detection and removal of different types of noises such as Gaussian noise, impulse noise etc [6]. Van De Ville et al[15] proposed a Gaussian noise reduction filter that performs weighted averaging of pixel intensity differences in which the weights are determined by the fuzzy directive. Here, the directive is defined in such a way that large variations indicate the presence of an edge and smaller variations are likely due to noises. A Noise Adaptive Fuzzy Switching Median Filter (NAFSM) is proposed in [8] that is able to filter out high densities of impulse noises. In the detection stage, twin peaks in the noise histogram are used to locate pixels that are likely to be corrupted with impulse noises. Fuzzy logic is then applied in the filtering stage to decide the pixel correction factors. Jian Wu and Chen Tang [9] proposed a Fuzzy Weighted Non-Local Means Filter for the removal of mixed Gaussian and random-valued impulse noise. A common feature of all these methods is that the fuzzy directives are estimated using linear membership functions. Although linear memberships are simple and intuitive, they often fail to capture the complexity of the underlying image property based on which filtering decisions are to be made. By devising non-linear membership curves, more application specific fuzzy directive estimates may be obtained that enabling refined filtering decisions [10]. In this paper, a novel non-linear membership function is proposed for image denoising which provides a better distinction between regions of images with edges and noises.

The rest of this paper is organized as follows. Section 3 describes the working of fuzzy based averaging filter that makes use of a linear membership function for estimating the fuzzy directive. In section 4, the proposed non-linear membership function is introduced and its mathematical properties are analyzed. Image quality metrics obtained for various intensities of additive noises and the simulated images are shown in section 5. Section 6 briefly summarizes the central idea of the paper.

3. FUZZY FILTER

A Fuzzy based averaging filter as proposed by D. Van De Ville [15] is discussed in this section. The denoising process is carried out in mainly three stages.

3.1. Edge Correction

Edges are regions within the image where there is a sharp difference in intensity values of neighboring pixels. Initially, the differences in pixel intensity values are computed. If each of these measured differences contributes to the overall pixel correction equally, then it is simply a basic averaging filter without edge preservation. Edge correction is done based on the observation that if the value of pixel intensity difference in a particular direction is sufficiently large, then it is highly likely that the difference is due to the presence of an edge in that direction rather than due to noises. Intensity differences due to noises in the image will not be as prominent as edges and therefore has smaller magnitudes. A linear fuzzy membership function 'small' is defined.

$$\mu_1(x) = \begin{cases} 1 - \frac{|x|}{s}, & if \quad |x| < s \\ 0, & else \end{cases} \qquad (1)$$

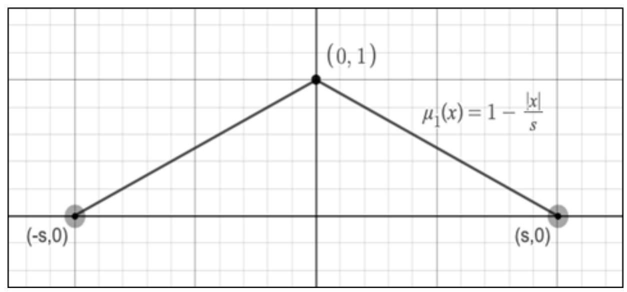

Figure 1**:** Linear Fuzzy Membership Function μ_1

The value "$\boldsymbol{s}$" determines the spread of the membership function. It is a measure of the maximum deviation that may be a result of noises.

3.2. Fuzzy Smoothing

The membership grade determines the fraction of the measured difference of neighboring pixels(x) added to the overall correction of the pixel being smoothed. For regions of noises, the measured intensity difference will be small compared to differences due to edges, and require greater correction. Likewise, in regions where edges are present corrections performed should be minimum. This distinction is achieved through the membership function 'small' (μ_1).

3.3. Averaging in All Directions

The correction component in a particular direction D is given by the product: $\Delta C_D = x \times \mu_1(x)$ (2)

Where x is the measured pixel intensity difference in direction D and μ_1 is the corresponding membership degree of x. Membership grades of pixel intensity differences due to noises are high, so the correction component will include a larger fraction of the measured difference. On the other hand, membership grades of pixel intensity differences due to edges are low and hence only a very small fraction of these differences are included in the correction component. After obtaining ΔC_D in all directions in set **D**={N,S,E,W,NE,NW,SE,SW}, the average value is computed to obtain total correction

$$\Delta C = \frac{1}{|\mathbf{D}|}\sum_{d \in D} \Delta C_d \qquad (3)$$

4. PROPOSED MEMBERSHIP FUNCTION

This paper proposes a novel non-linear fuzzy membership function $\mu_2(x, \phi_1, \phi_2)$ as a replacement for the existing Linear FMF μ_1 in order to improve noise removal and edge retention capability of the filter. The Degree of Membership (DoM) or the value returned by the membership function may be thought of as a penalty that determines the fraction of pixel difference that is included in the total correction of that pixel. Rather than using a linear FMF μ_1 which penalizes pixel value differences(x) due to noises and edges in a linear manner, better filtering may be achieved through the use of a non-linear FMF such that x values closer to origin are assigned a higher membership grade/penalty in comparison to μ_1 as they are most certainly noise deviations. A higher penalty implies greater filtering in this neighborhood. Likewise, x values closer to ±s that are likely to be due to image edges are assigned lower penalties compared to μ_1. Thus the contribution or fraction of x added to the overall correction when compared to the linear FMF$\mu_1$is lower, thus further preserving the edges. ϕ_1, ϕ_2 are the two parameters that provide the non-linearity required for better filtering. Analysis on how the parameters affect the curvature of the FMF is discussed in the subsequent sub-chapter (4.2).

4.1. Mathematical Formulation

The proposed non-linear Fuzzy membership function (FMF) is defined as follows:

$$\mu_2(x, \phi_1, \phi_2) = \begin{cases} \left(1 - \left(\frac{|x|}{s}\right)^{\phi_2}\right)^{\phi_1} & , if\ |x| < s \\ 0 & , else \end{cases} \qquad (4)$$

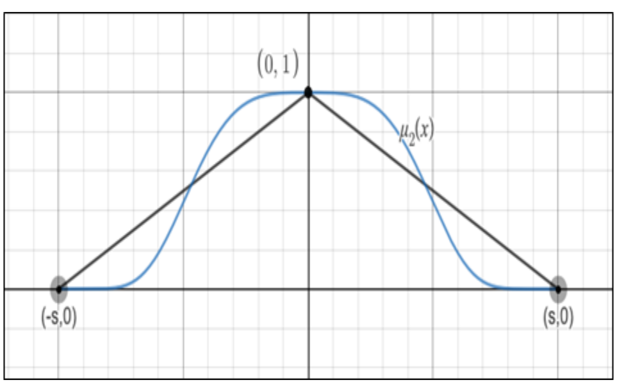

Figure 2: Non-Linear Fuzzy Membership Function μ_2

Properties of FMF μ_2 are as follows:

- μ_2 is continuous throughout the interval [-s, +s], implying there are no breaks in the curve and there exists a unique membership value ∀x in the interval.
- At $\phi_1 = 1$ and $\phi_2 = 1$, $\mu_2 = \mu_1$ ie, the new FMF is an extension of the previously discussed (Fig. 1) Linear FMF μ_1
- $\mu 2(0) = 1$, $\mu 2(\pm s) = 0$.The boundary conditions are similar, i.e., the points at which the curve $\mu_2$intersects the x and y axis are similar to that of μ_1. The maximum value of μ_2 is 1 at x=0 and minimum value of μ_2 is 0 at x = ±s.
- $0 \le \mu_2 \le 1, \forall x$. The range of μ_2 is [0, 1].

4.2. Analysis of FMF Parameters

The non-linear FMF parametersϕ_1, $\phi_2$determines the shape of the membership curve. The changes in the curve shape brought on by increasing the value of each parameter while fixing the other is analyzed in this section.

Case 1: On fixing the value of ϕ_1 at 1 and gradually increasing ϕ_2, the following plots are obtained (Fig. 3).

As the value of ϕ_2 is increased, the curve is shifted in the upward direction. It is observed that membership curves with higher ϕ_2 value return a significantly higher degree of memberships for x values, especially those in the neighborhood of $x = 0$. In the context of the noise filter, x values in this neighborhood (near the origin) are a result of noises. By increasing ϕ_2 essentially allows us to increase the penalties (fraction of the pixel added to the overall correction value), thus increasing the extent of smoothing in the image region identified to be noisy. However, very large values for ϕ_2 are not desirable for the image filter as for such curves, even pixel differences caused due to image edges will also be assigned a high DoM or penalty.

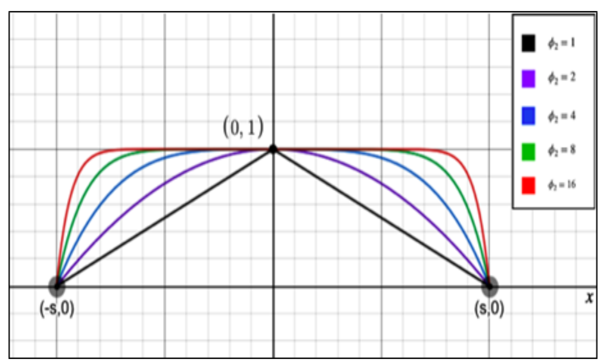

Figure 1: Family of FMF curves $\boldsymbol{\mu_2}$ with $\boldsymbol{\phi_1}$fixed at 1

Case 2: On fixing the value of ϕ_2 at 1 and gradually increasing ϕ_1, the following plots are obtained (Fig. 4).

As the value of ϕ_1 is increased the curve is shifted in the downward direction. A similar observation can be made regarding how the membership curves with higher ϕ_1 value return a significantly lower degree of memberships for x values, especially those in the neighborhood of $x = \pm s$. Based on the argument made earlier, x values with magnitude closer to $x = \pm s$ (towards the tail) are pixel differences likely to be caused due to edges in the image. Increasing ϕ_1 allows us to decrease the penalties, thus reducing the extent of smoothing done. Also, curves with very large values for $\phi_1$assign low penalties even for pixel differences corresponding to noises and are not desirable for the filter.

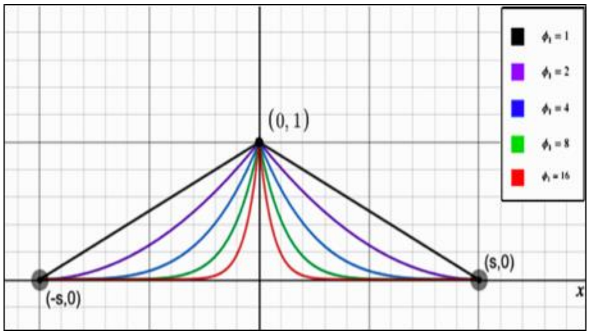

Figure 2 Family of FMF curves $\boldsymbol{\mu_2}$ with $\boldsymbol{\phi_2}$ fixed at 1

4.3. Guidelines For Selecting Parameter Values

A few general guidelines for selecting the parameters for ideal filtering are established:

- If the value assigned to the inner exponent (ϕ_2) is considerably high, then the inner expression, $\left(1 - \left(\frac{|x|}{s}\right)^{\phi_2}\right) \approx 1$. Thus, property associated with ϕ_2, i.e., how far the curve is shifted upwards, tends to dominate. Ensure $\phi_2 \ll \phi_1$to avoid such skewed behavior.
- The magnitude of both the parameters should be comparable to avoid property of the larger parameter from dominating.
- The two parameters also influence the slope at which μ_2 intersects μ_1 as $|slope| \propto \phi_1\phi_2$.This relation can be verified by differentiating the curve μ_2. Since a steep slope of the FMF helps better differentiate the regions of noise and edges, $\phi_1, \phi_2 \gg 1$ [Fig. 5]

$$\mu_2(x, \phi_1, \phi_2) = \left(1 - \left(\frac{x}{s}\right)^{\phi_2}\right)^{\phi_1}$$

$$\Rightarrow \quad ln(\mu_2) = \phi_1 . ln\left(1 - \left(\frac{x}{s}\right)^{\phi}\right)$$

Since $\frac{|x|}{s} < 1 \text{ and } \phi_2 > 1$, The Maclaurin series expansion of $ln\left(1 - \left(\frac{|x|}{s}\right)^{\phi_2}\right)$ converges.

$$ln(\mu_2) = -\phi_1 . \sum_{n=1}^{\infty}\left[\frac{1}{n} . \left(\frac{x}{s}\right)^{n\phi_2}\right]$$

$$\Rightarrow \quad \frac{d\mu_2}{dx} = -\frac{\phi_1\phi_2\mu_2}{s}\sum_{n=1}^{\infty}\left[\left(\frac{x}{s}\right)^{n\phi_2 - 1}\right]$$

$$\Rightarrow \quad slope \propto -\phi_1\phi_2 \qquad (5)$$

A region of accepted curves is defined as shown in Fig. 6. The shaded area shows the family of curves that follows our requirement for effective image filtering. Curves lying further up of this region assign large penalties even for pixel differences corresponding to edges which may lead to undesirable blurring of image edges. Similarly, the curves lying below this region assign very low penalties even for pixel differences corresponding to noises which result in poor filtering. All the plots within the shaded region are generated by fixing the value of $\phi_1 = 11$ and varying ϕ_2). The upper bound and lower bound of the accepted region in terms of ϕ_2 are ϕ_2= 4.8 and ϕ_2= 2.5.

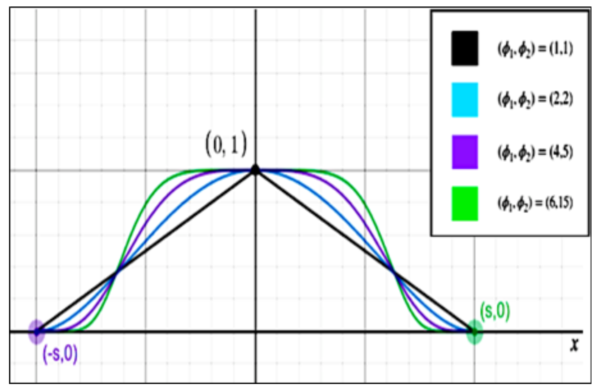

Figure 5: Demonstrates the relation between slope and magnitude of parameter values. Higher values of ϕ_1 ,ϕ_2 values imply a steeper slope.

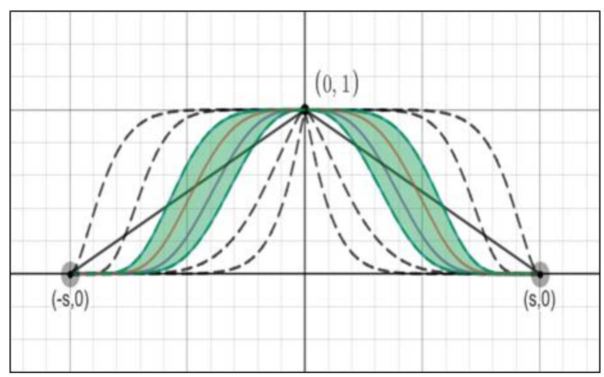

Figure 6: Shaded region describes the family of accepted FMF curves

5. RESULTS AND DISCUSSIONS

In this subsection, we compared the results of the naive Averaging filter, Fuzzy filter with the linear membership function μ_1, and the proposed filter with non-linear membership function μ_2. The complete experiment is conducted in Matlab [16] R2018b. The algorithms are tested out on standard Cameraman and Peppers image. Gaussian noise of varying intensities is introduced to the image to study the effectiveness of the image filters (Fig. 9). The image quality metrics obtained are for both the images are compared in tables Table I and Table II. Observing the results obtained given in the tables, the metric values, especially Structural Similarity Index (SSIM), clearly shows an improvement in the case of the proposed non-linear fuzzy filter compared to the other filters This concurs the superior performance of the proposed filter. The time complexity of the modified filter is the same as that of the averaging filter, O(nm) for an n × m image.

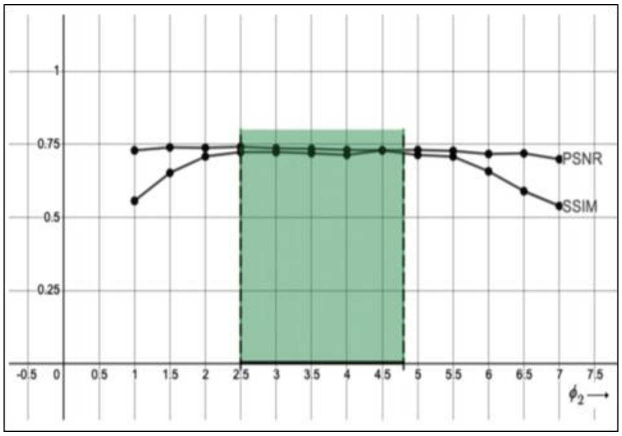

Figure 7: Plot of PSNR (Normalised) and SSIM values as a function of parameter $\boldsymbol{\phi_2}$ with $\boldsymbol{\phi_1}$ fixed at 11. Shaded region corresponds to the optimal range.

Figure 8: Input images (a) cameraman.tif (b) peppers.png

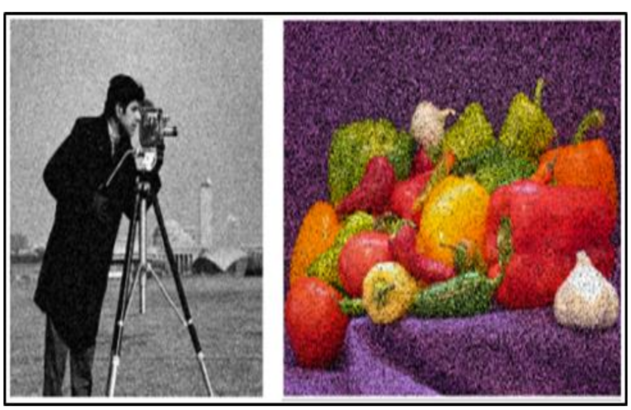

Figure 9: Input images with 10% noise

5.1. Image Metrics

a) MSE (Mean Square Error): MSE is the cumulative squared error between the filtered and the original image. It represents the mean of the sum of the squared differences of the intensity values between the reference and the original image. For two images of dimension $M \times N$,

$$MSE = \frac{\sum_{M,N}[I_1(m,n) - I_2(m,n)]^2}{M * N} \quad (6)$$

b) MAXERR (Maximum absolute squared deviation): The maximum absolute deviation around an arbitrary point is the maximum of the absolute deviations of a sample from that point. Here the maximum value of absolute squared deviation is taken as the maximum absolute squared deviation.

c) PSNR (Peak Signal to Noise Ratio): PSNR gives the ratio of the value of the signal to the value of noise in an image. It is given in decibel (dB) values. The PSNR values are calculated using the equation:

$$PSNR = 10log_{10}\left(\frac{I_{max}^2}{\text{MSE}}\right) dB \quad (7)$$

Where, I_{max}^2 is the maximum pixel intensity value in the reference image and MSE is the mean squared error The unit of measurement is Decibels (dB).

d) SSIM (Structural Similarity Index): The SSIM [17] quality assessment index is based on the computation of three terms, namely the luminance term, the contrast term and the structural term. SSIM is then a weighted combination of those comparative measures, and is a good indication of edge retention.

$$l(x,y) = \frac{2\mu_x\mu_y + C_1}{{\mu_x}^2 + {\mu_y}^2 + C_1} \quad (8)$$

$$c(x,y) = \frac{2\sigma_x\sigma_y + C_2}{{\sigma_x}^2 + {\sigma_y}^2 + C_2} \quad (9)$$

$$s(x,y) = \frac{\sigma_{xy} + C_3}{\sigma_x + \sigma_y + C_3} \quad (10)$$

$$SSIM(x,y) = \left[l(x,y)^{\propto}.c(x,y)^{\beta}.s(x,y)^{\gamma}\right] \quad (11)$$

Where $\mu_x, \mu_y, \sigma_x, \sigma_y, and\ \sigma_{xy}$ are the local means, standard deviations, and cross-covariance for images x, y.

e) NAE (Normalized Absolute Error): This quality measure can be expressed as follows:

$$NAE = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n}(|A_{ij} - B_{ij}|)}{\sum_{i=1}^{m}\sum_{j=1}^{n}A_{ij}} \quad (12)$$

Here, A is the reference image and B is the estimation of image A.

f) L2RAT (Energy Ratio): It is the ratio of the squared norms of the two images. For ideal filtering, L2RAT is 1.

(a) 20% Gaussian noise

(b) Filtered using averaging filter

(c) Filtered using Fuzzy filter with Linear membership function

(d) Filtered using Fuzzy filter with Non-Linear membership function

Figure 10: Filtered images simulated with 20% Gaussian noise; ”cameraman.tif”

(a) 40% Gaussian noise

(b) Filtered using averaging filter

(c) Filtered using Fuzzy filter with Linear membership function

(d) Filtered using Fuzzy filter with Non-Linear membership function

Figure 11: Filtered images simulated with 40% Gaussian noise; ”cameraman.tif”

(a) 20% Gaussian noise

(b) Filtered using averaging filter

(c) Filtered using Fuzzy filter with Linear membership function

(d) Filtered using Fuzzy filter with Non-Linear membership function

Figure 12: Filtered images simulated with 20% Gaussian noise; ”peppers.png”

(a) 40% Gaussian noise

(b) Filtered using averaging filter

(c) Filtered using Fuzzy filter with Linear membership function

(d) Filtered using Fuzzy filter with Non-Linear membership function

Figure 13: Filtered images simulated with 40% Gaussian noise; ”peppers.png”

Filter Used	**Gaussian Noise**	**MSE**	**MAXERR**	**PSNR**	**SSIM**	**NAE**	**L2RAT**
Averaging Filter	10%	0.0063	0.6676	69.2882	0.5770	0.1050	0.9924
	20%	0.0086	0.6808	68.7805	0.5069	0.1211	1.0216
	30%	0.0089	0.6890	66.3422	0.4806	0.1209	1.0212
	40%	0.0102	0.7300	60.6654	0.4189	0.1356	1.0396
Filter with Linear FMF	10%	0.0027	0.4333	73.5584	0.6655	0.0845	1.170
	20%	0.0037	0.4961	72.6744	0.6684	0.0821	1.0359
	30%	0.0045	0.5612	70.2427	0.6412	0.1108	1.0160
	40%	0.0048	0.5823	69.0951	0.6238	0.1288	1.0189
Filter with Non-Linear FMF	**10%**	**0.0022**	**0.4170**	**74.6947**	**0.7607**	**0.0677**	**1.0211**
	20%	**0.0027**	**0.4487**	**73.3840**	**0.7059**	**0.0807**	**1.0189**
	30%	**0.0035**	**0.4878**	**73.8510**	**0.7055**	**0.0787**	**1.0170**
	40%	**0.0040**	**0.5454**	**71.2401**	**0.6860**	**0.1102**	**1.0203**

Table 1. Comparison of Denoising Filters; "Cameraman.tf"

Filter Used	**Gaussian Noise**	**MSE**	**MAXERR**	**PSNR**	**SSIM**	**NAE**	**L2RAT**
Averaging Filter	10%	0.0014	0.4389	76.6173	0.7348	0.0581	0.917
	20%	0.0025	0.4674	72.5604	0.6744	0.077	0.9922
	30%	0.0034	0.5110	68.766	0.5710	0.0912	1.102
	40%	0.0045	0.5729	65.0013	0.4612	0.1244	1.023
Filter with Linear FMF	10%	0.0010	0.2826	78.0201	0.7964	0.0593	1.0110
	20%	0.0023	0.3225	77.5815	0.7091	0.0688	1.0112
	30%	0.0030	0.4450	72.7140	0.6776	0.0752	1.0170
	40%	0.0037	0.5031	70.0588	0.6390	0.0695	1.0243
Filter with Non-Linear FMF	**10%**	**0.0007**	**0.2666**	**79.6113**	**0.8710**	**0.0419**	**1.0112**
	20%	**0.0015**	**0.3255**	**77.9288**	**0.8440**	**0.0501**	**1.0020**
	30%	**0.0022**	**0.3920**	**74.6290**	**0.7811**	**0.0657**	**1.0140**
	40%	**0.0031**	**0.4034**	**71.0013**	**0.7255**	**0.0774**	**1.0201**

Table 2. Comparison of Denoising Filters; "Peppers.png"

6. CONCLUSION

Averaging filters, although a very fast approach for image denoising, causes blurring of edges in images. By introducing ideas in fuzzy logic, the extent of smoothing in regions where edges are present is limited. Currently, fuzzy based algorithms make use of a FMF to make this distinction between noises and edge deviations. Tuning the parameters of the proposed membership function based on the established guidelines enables the algorithm to be stricter to noises and at the same time less sensitive to regions where edges are likely. This in turn, results in a better denoising. The time complexity after the modification is still O(n × m) Hence, a fast and simple denoising algorithm which can adapt to images by little user interaction is developed with similar time complexity to that of the basic averaging filter. Significant improvement in the values of various image quality metrics aligns with this conclusion.

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