Research Article

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Robust Gaussian Noise Detection and Removal in Color Images using Modified Fuzzy Set Filter

Abstract: In the data collection phase, the digital images are captured using sensors that often contaminated by noise (undesired random signal). In digital image processing task, enhancing the image quality and reducing the noise is a central process. Image denoising effectively preserves the image edges to a higher extend in the flat regions. Several adaptive filters (median filter, Gaussian filter, fuzzy filter, etc.) have been utilized to improve the smoothness of digital image, but these filters failed to preserve the image edges while removing noise. In this paper, a modified fuzzy set filter has been proposed to eliminate noise for restoring the digital image. Usually in fuzzy set filter, sixteen fuzzy rules are generated to find the noisy pixels in the digital image. In modified fuzzy set filter, a set of twenty-four fuzzy rules are generated with additional four pixel locations for determining the noisy pixels in the digital image. The additional eight fuzzy rules ease the process of finding the image pixels, whether it required averaging or not. In this scenario, the input digital images were collected from the underwater photography fish dataset. The efficiency of the modified fuzzy set filter was evaluated by varying degrees of Gaussian noise (0.01, 0.03, and 0.1 levels of Gaussian noise). For performance evaluation, Structural Similarity (SSIM), Mean Structural Similarity (MSSIM), Mean Square Error (MSE), Normalized Mean Square Error (NMSE), Universal Image Quality Index (UIQI), Peak Signal to Noise Ratio (PSNR), and Visual Information Fidelity (VIF) were used. The experimental results showed that the modified fuzzy set filter improved PSNR value up to 2-3 dB, MSSIM up to 0.12-0.03, and NMSE value up to 0.38-0.1 compared to the traditional filtering techniques.

Keywords: Denoising, digital image processing, fuzzy filter, fuzzy logic, Gaussian noise

1 Introduction

In recent decades, the digital images are playing an important role in numerous applications like computer vision, medical imaging, biometrics, etc. and also in the field of engineering science: geographical systems and astronomy [1, 2]. Due to intrinsic thermal fluctuations, imperfect device data collection and transmission, imperfection of lens device and external interface, noise is introduced inevitably in the captured digital images [3, 4]. Image denoising is a key procedure for restoring the noiseless image from the noisy observations that helps in preserving the edges and textures present in the digital images [5, 6]. Image denoising is considered as a necessary step in texture analysis, feature extraction and segmentation [7]. There are many denoising methodologies available for eliminating noise from the digital images. The conventional denoising algorithms have been developed by considering the parameters like noise and artifacts. The existing denoising methods are categorized into two types such as nonlocal self-similarity based methods and conventional

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local prior based methods. Mostly, the existing methods concentrate only on local priors, so their performances are inadequate [8–10].

Image filtering is another important technique in image denoising that alters the image features (size, color, shading, etc.) for smoothening the digital images [11]. The filtering denoising methodologies has two steps, those are noise reduction filter adjusts the pixels and classifies as noise-corrupted and then the impulse detector classifies the image pixels as noise-free or noise-corrupted. The three major types of noises exist in digital images are additive noise, multiplicative noise, and impulse noise [12]. Generally, the impulse noise is characterized by a few portions of image pixels that corrupt and leaves the remaining pixels unchanged. In addition, it is more challenging to remove additive and multiplicative noise from the digital images, because the noise intensity varies with the signal intensity (for instance, speckle noise) [13]. In order to remove these noises, several filtering techniques developed, those are median filter, Gaussian filter, fuzzy filter, etc. [14, 15]. The existing conventional filters are effective to eliminate the noise, but also it fails to preserve the image details, due to blurring at the edges. The concerns of traditional fuzzy filtering approaches are detailed below.

- An iterative based adaptive fuzzy filter is used for eliminating the salt and pepper noise in the digital images [16]. The drawback of this approach is assigning weight value to the good pixels in the window by using the inverse distance weight function. Hence, the developed fuzzy filter fails to preserve the digital image details.
- An effective noise reduction method named as adaptive fuzzy switching median filter is employed for digital image denoising [17]. This technique is only applicable for the impulse noise removal, not for continuous noise, low frequency noise, etc.
- Additionally, expert knowledge requires for designing the member function and selecting the suitable rules in the fuzzy system. Otherwise, the issues lie with weighting of good pixels leads to the loss of actual image details.

To overcome the above-mentioned drawbacks, a modified fuzzy set filter is proposed for eliminating Gaussian noise from the digital images. Gaussian noise is a statistical noise having a probability density function equal to the normal distribution, which is also named as Gaussian distribution. Generally, the fuzzy filter comprises of two essential factors; initially the filter calculates "fuzzy derivative" to reduce variations in the digital images. Secondly, the membership functions (small, positive, and negative) are utilized based on the noise level to accomplish fuzzy smoothing. In modified fuzzy set filter, after computing fuzzy derivative, a set of twenty-four fuzzy rules are generated with truth values for determining the correction term or noisy pixels. In this research, additional four pixel locations added to the fixed directions, especially for South West (SW), South East (SE), North East (NE), and North West (NW) directions. Hence, the generated twenty-four fuzzy rules mathematically represented in Table 1. If the mean of the truth-value satisfies the threshold value, averaging is performed. The residual noiseless pixels are retained by indicating the pixel as edge. The additional four pixel locations will ease the process of finding the pixels, whether it required averaging or not. Instead of using a larger window to achieve better results for heavier noise, the extra four pixel locations (each includes two fuzzy rules) consider more corner pixel information for estimating the amount of noise. The detailed description about modified fuzzy set filter is given in the section 3.

This research paper is arranged as follows. In section 2, several recent image denoising methodologies are surveyed. In section 3, explanation about modified fuzzy set filter is described for achieving a better outcome. In section 4, execution of the modified fuzzy set filter is done and the comparative analysis is performed between the proposed and existing methods. The conclusion is made in section 5.

2 Literature Survey

The researchers have developed several research techniques on image denoising. This sub-section describes a few important contributions to the existing literatures.

X. Zhang [18] presented an effective image denoising methodology based on the local Weiner filter. In this research, the noisy images were decomposed by utilizing Non-Subsampled Shearlet Transform (NSST), because it is an active multi-directional and multi-scalable analyzing tool in image denoising. The high frequency NSST coefficients were denoised by utilizing a shrinkage function on the basis of Wiener filter. In the new shrinkage function, the local Wiener filter was used by employing Linear Expansion of Thresholds and Stein's Unbiased Risk Estimate (LET-SURE) methodology. At last, the inverse-NSST was used for obtaining the denoised image. In the experimental stage, the developed methodology delivered better performance related to the existing wavelet based methodologies. The developed methodology is subjected to human error, as only classical image databases were considered for experimental analysis and not real time images. In addition, a new image denoising method was presented by J. Liu *et al.* [19] using multidirectional shrinkage and sparse representation of the edges. The sparsity improvement was achieved by utilizing directionlet transforms, which was constructed with the edge directions. The directionlet transform was performed in dissimilar directions for every pixel, so several estimates were obtained in that one of which was optimal. The final denoised output image was achieved by averaging the weight value of all individual estimates. The experimental result confirmed that the developed methodology effectively preserved the information (image texture and edges) and removed the noise compared to the other multi-directional wavelet methods. The semi-supervised methodology maximizes the semantic gap between the image feature values, which leads to poor detection rate.

K. Panetta *et al.* [20] presented a new idea of the Sequence-to-Sequence Similarity (SSS) measure to determine the similarity content (edge information) between the images. The developed methodology completely depends on the block and pixel similarity. For addressing the image denoising problems, the new SSS filter utilized the edge information in the denoised or corrupted image. The developed methodology's performance was experimented by using different images with a variety of Gaussian noise levels. In the experimental section, the developed methodology was experimented quantitatively and visually. The developed framework showed an effective outcome compared to the previous block-to-block similarity and pixel to pixel similarity. In this research, it was so difficult to remove the machinery noises, due to lower level alignment. Additionally, a new algorithm was developed by H.K. Rafsanjani, *et al.* [21] to select the diffusion coefficients using the gradient magnitude and residual local power. The developed algorithm effectively preserved the image details like edges and textures, because the texture region corresponds to the value of local power residue. For evaluating the developed algorithm performance, a variety of experiments were performed by means of visual quality, universal quality index, visual information, mean structural similarity and PSNR. The developed algorithm was linear in nature, so the diffusion coefficients were constant that leads to isotropic diffusion, and therefore it blurs the image edges to some extent.

Q. Guo, *et al.* [22] developed a simple denoising system using the low rank approximation and the non-local self-similarity. Initially, the similar image patches were classified by employing block matching scheme to generate the same patch groups. Then, each similar patched group was factorized by Singular Value Decomposition (SVD). Finally, a denoised grayscale image was created by combining all processed patches. Experimental outcome confirmed that the developed technique out-performed the existing schemes by means of PSNR and patch size. Generally, the fixed wavelet decomposition fails to provide an adaptive sparse representation of a complex image. In addition, an effective methodology (cohesive super-pixel) was presented by P. Fu *et al.* [23] to decompose the noisy image into patches for increasing the homogeneity. Additionally, a new pixel based similarity measure was developed for making the cohesive super-pixel method more robust to noise. Then, they combined the histogram based homogeneous super-pixel selection and the filter based noise level estimation to determine the noise level accurately in the digital image. Extensive experiments were performed on the "Fish" image in the Berkeley segmentation database (BSD) database for demonstrating the effectiveness of the developed methodology. A major concern in the developed methodology was more complex to identify the projection of free space. Free space can able to provide better discriminant ability in image feature estimation.

J. Bai, and X.C. Feng, [24] introduced generalized anisotropic diffusion equation for image denoising. Initially, a new derivative (G-derivative) was utilized for generalizing the anisotropic diffusion equation using Fourier transform. All the G-derivation operators were ring like structure and the semi-group property

of G-derivation contains semi-group property of fractional derivative. Therefore, the resultant generalized anisotropic diffusions were the generalized order of fractional anisotropic diffusions. A validation result confirmed that the developed technique was very effective related to the existing schemes. A major issue in the developed methodology was how to preserve the image edges, while reducing the noise. Additionally, R. Hao, and Z. Su, [25], developed a new patch based methodology for recovering a low rank tensor by using low-rank matrix factorization. Additionally, the lagrangian alternating minimization methodology was implemented to identify the un-known rank. The developed method was applied to multi-frame image denoising by exploiting the non-local self-similarity. Experimental outcome showed that the developed method effectively preserves the sharpness of essential image structures compared to the existing image denoising methodologies. The outcome of this research was highly volatile and subject to the human assumptions and intervention, while estimating the noise.

K.B. Khan, *et al.* [26] developed an Adaptive Trimmed Mean Autoregressive (ATMAR) method to denoise the medical images from Poisson noise. Initially, the noisy digital images were divided into smaller portions and then ATMAR method was applied to find the central pixel value of the digital image. In addition, the adaptive autoregressive coefficients were updated by sliding the windows with 60% shift. At last, power law transformation was used to stretch the contrast of the image. In the experimental section, the developed method showed better outcomes compared to the prior research works in light of MSE, correlation, SSIM and PSNR. A key concern in the adaptive trimmed mean filter is to select the optimal alpha parameter for a specific noise type. In addition, K.B. Khan, *et al.* [27] presented a new weighted gradient filter to denoise the medical images from Poisson noise. In a predetermined window, weighted gradient filter was utilized to calculate the gradient value, and then the center pixel gradient values were averaged. In this research study, the developed method performance was evaluated on both multimedia and biomedical images. Hence, the developed filtering method was computationally effective and faster compared to the existing filtering techniques. In contrast, a major issue with weighted gradient filter is the cost of increment on running times. To overcome the above-mentioned issues, a modified fuzzy set filter is proposed to enhance the performance of image processing applications like object extraction, segmentation, etc.

3 Proposed Methodology

Denoising the digital image is an active research area in the field of digital image processing. In these days, the digital images are used in many applications for the intended operations like feature extraction, segmentation, dimensionality reduction, etc. Therefore, it is necessary to select an appropriate (noiseless) digital image; if the data are not acquired satisfactorily then the intended operations may not be achievable. Generally, the fuzzy denoising is accomplished by mapping a fuzzy plane into the image gray level intensities by utilizing membership function. Then, modify the membership functions for image enhancement and map the fuzzy plane into image gray level intensities. The modified fuzzy set filter consists of five steps; image collection, image fuzzification, membership function, fuzzy logic-fuzzy set theory and defuzzification. The working procedure of modified fuzzy set filter is presented in Figure 1. The brief description about modified fuzzy set filter is given below.
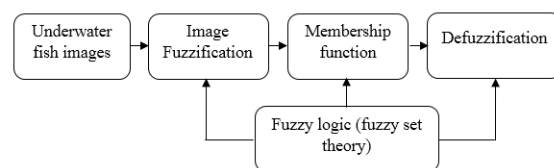

Figure 1: Work flow of modified fuzzy set filter

In this research paper, a modified fuzzy set filter is developed for eliminating noise from the digital images I, which are corrupted by Gaussian noise. At first, the noise level is estimated from the images, which are going to be denoised. Then, fuzzy differential is calculated to classify the local variations of image features like noise and edges. In addition, the membership functions are applied on the basis of noise level and then fuzzy smoothing is performed for image denoising. Based on the local image properties, the fuzzy rules are generated. The generated fuzzy rules along with membership function evaluates the level of smoothing. The membership function is altered after every iteration for small and the membership function is fixed for both positive and negative [28]. Generally, in fuzzy set filter, sixteen fuzzy rules are generated for identifying the noisy pixels in the digital image. In modified fuzzy set filter, twenty-four rules are generated by the truth-values. If the mean of truth-value satisfies the threshold value and then averaging is performed. The remaining noiseless pixels are retained by indicating the pixel as edge. Graphical depiction of fuzzy set filter and modified fuzzy set filter patterns are denoted in Figure 2.
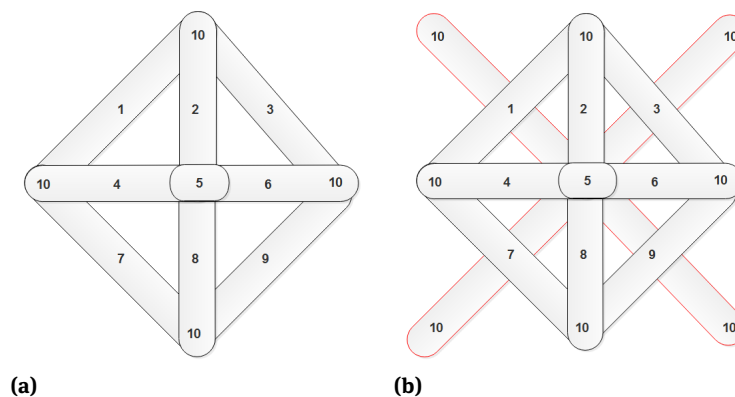

(a) (b)

Figure 2: a) Fuzzy set filter pattern, and b) modified fuzzy set filter pattern

3.1 Fuzzy Differential

Normally, the fuzzy filter recovers the original digital image from the noise and retains the important image features like edges by averaging an image pixel with neighborhoods. Initially, the fuzzy filter classifies the random variations generated by image structures and noise. The 3×3 image pixel has eight directions, such as N, S, W, E, NW, NE, SW, and SE. For each pixel, a value is calculated to specify the amount of fuzzy differential in a given direction. The respective value is calculated using the generated fuzzy rules. Graphical representation of central pixel with eight neighborhood pixels is denoted in Figure 3.

- If the fuzzy differential is high, the pixel is considered as edge.
- If the fuzzy differential is low, the pixel is assumed as noisy pixel.

NW	N	NE
W	p(x, y)	E
SW	S	SE

Figure 3: Central pixel $p(x, y)$ with eight neighborhood pixel

A simple fuzzy differential is obtained by computing the difference between central pixel $p(x, y)$ and its neighbor pixels in the direction. The differential value is represented as $d_D(x, y)$. The membership functions

(small, positive, and negative) are graphically represented in Figure 4, where L is denoted as an effective parameter that is determined using effective filtering approach. The pixels involved to determine the fuzzy differential in each direction are given in Table 1 [15].
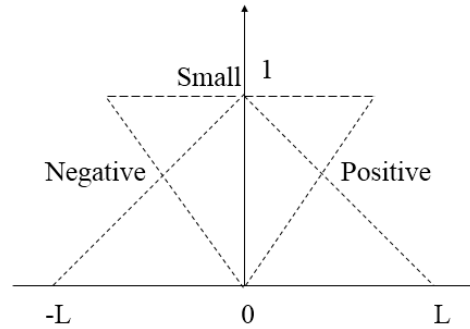

Figure 4: Graphical illustration of membership function

Table 1: Pixels used for calculating the fuzzy differential in every direction

Direction	Position	Set (x, y)
NW	(x-1, y-1)	$\{(-1,1), (0,0), (1,-1)\}$
		$\{(-1,-1), (0,0), (1,1)\}$
W	(x-1, y)	$\{(0,1), (0,0), (0,-1)\}$
SW	(x-1, y+1)	$\{(1,1), (0,0), (-1,-1)\}$
		$\{(-1,1), (0,0), (1,-1)\}$
S	(x, y+1)	$\{(1,0), (0,0), (-1,0)\}$
SE	(x+1, y+1)	$\{(1,-1), (0,0), (-1,1)\}$
		$\{(1,1), (0,0), (-1,-1)\}$
E	(x+1, y)	$\{(0,-1), (0,0),(0,1)\}$
NE	(x+1, y-1)	$\{(-1,-1), (0,0), (1,1)\}$
		$\{(-1,1), (0,0), (1,-1)\}$
N	(x, y-1)	$\{(-1,0), (0,0), (1,0)\}$

3.2 Pixel Correction using Fuzzy Filter

In this sub-section, the purpose of utilizing fuzzy differential or fuzzy derivative is detailed effectively. If suppose, an edge passes through the neighborhood direction (NE-SW), the fuzzy differential indicates the differential value $d_{SE}(x, y)$ and the neighborhood pixels are orthogonal to the edge direction that are considered to be high. Table 1 denotes the pixels used for calculating the fuzzy differential in every direction. In case, if two among three differentials are small, then it is safe to believe that no edge is present in the respective direction. The fuzzy differential values are determined by formulating the fuzzy rule on the basis of observation. Further, calculate the values that show the amount to which the fuzzy differential is small in a certain direction, a fuzzy set small is represented in Figure 4.

In this research, L is represented as an effective parameter, which is determined by using effective filtering approach. In determining the degree of membership of the fuzzy differentials $df_D(x, y), D \in DIR$ to the set small, similar twelve such rules are generated. These rules are generated by using AND and OR operator. For instance, the value of fuzzy derivative $df_N(x, y)$ for the pixel (x, y) in the N direction is determined by apply-

ing the following rule; if ($d_N(x, y)$ is small, and $d_N(x - 1, y)$ is small) or ($d_N(x, y)$ is small, and $d_N(x + 1, y)$ is small) or ($d_N(x - 1, y)$ is small, and $d_N(x + 1, y)$ is small), then $df_N(x, y)$ is small. Likewise, if ($d_N(x, y)$ is positive or negative, and $d_N(x - 1, y)$ is positive or negative) or ($d_N(x, y)$ is positive or negative, and $d_N(x + 1, y)$ is positive or negative) or ($d_N(x - 1, y)$ is positive or negative, and $d_N(x + 1, y)$ is positive or negative), then $df_N(x, y)$ is positive or negative.

In the application of differential, fuzzy defuzzification is not required for the membership degree small that is considered in the next phase (smoothing). The smooth pixel sets are identified by employing a fuzzy rule for every direction. The generated rules are used to identify the effective differential value by assuming no edges in the direction. Since, the fuzzy differential rule is used to check, whether the edge is available or not. Then, defuzzification is accomplished for filtering in order to get a smoothed image by averaging the pixel value. A fuzzy rule is utilized to determine, whether the pixels required averaging or not. To perform this process, the truth-value of each pixel for all directions is aggregated, which is mathematically denoted in the equations (1) and (2).

$$i = \begin{cases} 4 & 0 \le ne < 4 \\ 2 & 4 \le ne < 10 \\ 1 & ne \ge 10 \end{cases} \tag{1}$$

$$ne = \sigma \times \frac{\sqrt{(0.5) \times \pi}}{(6 \times (n - 2) \times (m - 2))} \tag{2}$$

Where, ne is represented as noise estimate, (m, n) are denoted as image rows and columns, i is represented as a threshold, and σ is achieved using a Laplacian of Gaussian mask on the digital image. Usually, the Gaussian noise appeared as white intensity pixel values in the image, which has a Probability Density Function (PDF) with normal or Gaussian distribution. Therefore, it is additive in nature and every pixel value in the noisy image is the addition of the original pixel with a random Gaussian distributed noise value. Hence, the PDF of Gaussian random value is indicated in equation (3).

$$p(z) = \frac{1}{\sqrt{2\pi}\sigma} e^{[-(z-\mu)^2/2\sigma^2]} \tag{3}$$

Where, σ and μ are indicated as standard deviation and mean, z is indicated as pixel value, $p(z)$ is denoted as Gaussian noise in the image, and π is 3.1416. The neighborhood pixels' mean is obtained in this section and considered as a new pixel, otherwise the original pixel is retained.

3.3 Effective Filtering Approach

Usually, the large window delivers better results, when the digital image I has more noise. In a few conditions, the large window losses the image features like edges and feature information. To address this concern, an effective filter is applied iteratively by altering the small membership function shape. After every iteration, the parameters are modified on the basis of noise level for reducing the smoothing amount. The digital image is categorized into small $n \times n$ non-overlapping blocks. For each n block, the standard deviation σ_{ij} is calculated. The minimum σ of non-overlapping block is identified that is represented as σ_{min}. At last, an effective parameter L is determined by multiplying an amplification factor $\forall$ with σ_{min}. The amplification factor $\forall$ is evaluated by using the equation (4), which is completely based on the image noise level.

$$\forall = \begin{cases} 1 & 0 \le ne < 4 \\ 3 & 4 \le ne < 10 \\ 4 & 10 \le ne < 20 \\ 6 & 20 \le ne < 30 \\ 7 & 30 \le ne < 40 \\ 10 & ne \ge 40 \end{cases} \tag{4}$$

The amplification factor $\forall$ is set proportional to the noise level for an effective denoising. Based on the noise estimate (ne), the number of iterations is decided. The equation (5) represents the condition for a number of iterations.

$$Iterations = \begin{cases} 1 & 0 \leq ne < 4 \\ 2 & 4 \leq ne < 50 \\ 3 & ne \geq 50 \end{cases} \tag{5}$$

Algorithm of modified fuzzy set filter

Step 1 Function d_D = Direction (I)

{

For Every Pixel p_{xy} in I

$\quad\quad d_N(x, y) = p(x - 1, y) - p(x, y)\,;$

$\quad\quad d_{NE}(x, y) = p(x - 1, y + 1) - p(x, y)\,;$

$\quad\quad d_{NW}(x, y) = p(x - 1, y - 1) - p(x, y)\,;$

$\quad\quad d_S(x, y) = p(x + 1, y) - p(x, y)\,;$

$\quad\quad d_{SE}(x, y) = p(x + 1, y + 1) - p(x, y)\,;$

$\quad\quad d_{SW}(x, y) = p(x + 1, y - 1) - p(x, y)\,;$

$\quad\quad d_E(x, y) = p(x, y + 1) - p(x, y)\,;$

$\quad\quad d_W(x, y) = p(x, y - 1) - p(x, y)\,;$

$\quad\quad d_D = [d_N d_{NE} d_{NW} d_S d_{SE} d_{SW} d_E d_W]\,;$

}

Step 2 Function L = Adaptation (I, $\forall$)

{

For non-over-lapping block, create a sliding window of size ($n \times n$)

$\quad\quad$for $x = 1 : n : row\ size$

$\quad\quad\quad\quad$for $y = 1 : n : column\ size$

$\quad\quad\mu_{xy} = \frac{(\sum I(x,y))}{(n \times n)}\,;$

$\quad\quad\sigma_{xy} = \sqrt{\frac{\sum (I(x,y) - \mu_{xy})^2}{(n \times n)}}\,;$

$\sigma_{min} = \min(\sigma_{xy})\,;$

$L = \forall \sigma_{min}\,;$

}

Step 3 Function $[I, \; ap]$ = Averaging $(d_D, \; I, \; L, \; i)$

{
For Every Pixel p_{xy} in I
    if $(d_D(x, y) < L)$ and $(d_D(previous) < L)$
    or $(d_D(x, y) < L)$ and $(d_D(next) < L)$
    or $(d_D(previous) < L)$ and $(d_D(next) < L)$ then
        $df_D(x, y) = 1 - \frac{d_D(x,y)}{L}$;
    else
        $df_D(x, y) = 0$;
    if $(df_D(x, y) < L)$ and $(df_D(x, y) <> 0)$ then
        Assign $c_D = 1$;
        Compute c_D for all directions;
  $ap(x, y) \sum c_D$;
  if $(ap(x, y) \geq i)$ then
        $D(x, y) = mean \{I(x, y), I(x - 1, y), I(x + 1, y),$
            $I(x - 1, y - 1), I(x + 1, y + 1), I(x + 1, y - 1),$
            $I(x - 1, y + 1), I(x, y - 1), I(x, y + 1)\}$;
}

Step 4 Function $I = Main(I)$

{
        $[d_D] = Direction(I)$
        Select $\forall, \; i$ using the Equations (1) and (4)
        $L = Adaptation(I, \; \forall)$
        D = Averaging $(d_D, \; I, \; L, i)$
        Compute PSNR, MSSIM, SSIM, MSE, UIQI, VIF and NMSE }

4 Experimental Analysis and Discussion

In this section, experimental result and discussion of modified fuzzy set filter is detailed and explained about the experimental set-up and performance measures. The modified fuzzy set filter's performance is also evaluated in light of comparative and quantitative analysis.

4.1 Experimental Setup

The modified fuzzy set filter was experimented by utilizing MATLAB (version 2017a) with 4 GB RAM, 3.0 GHz Intel i3 processor and 500 GB hard disc [29]. The modified fuzzy set filter's performance was compared with a few existing filters in order to estimate the efficiency of proposed filter. The performance evaluation of the modified fuzzy set filter was made under the circumstance of noise attack (Gaussian noise) in terms of PSNR, MSSIM, SSIM, MSE, UIQI, VIF and NMSE.

4.2 Performance Measure

In this research, PSNR, MSSIM, SSIM, MSE, UIQI, VIF and NMSE performance measures are utilized for comparing the performance evaluation of noisy image $k(x, y)$ and denoised image $k'(x, y)$. Usually, the PSNR value is utilized as a quality measurement between the denoised $k'(x, y)$ and noisy image $k(x, y)$. The high PSNR value determines the best quality of denoised image [30]. Mostly, the PSNR value is defined by MSE that is

mathematically denoted in equation (6),

$$MSE = \frac{1}{mn} \sum_{x=0}^{m-1} \sum_{y=0}^{n-1} \left\| k(x,y) - k'(x,y) \right\|^2 \tag{6}$$

Where, m and n are indicated as image dimensions (rows and columns) and $k(x,y)$ is denoted as the input image, $k'(x,y)$ is denoted as denoised image. Another criterion, which is used for evaluating the PSNR value is given in equation (7),

$$PSNR = 20 \, log_{10}(\frac{\max(k(x,y))}{\sqrt{MSE}}) \tag{7}$$

In addition, the effectiveness of modified fuzzy set filter is further analyzed by using the performance metrics like NMSE, MSSIM, and UIQI [31, 32], which are mathematically given in the equations (8), (9), (10), and (11).

$$NMSE = \frac{\sum_{x=0}^{m-1} \sum_{y=0}^{n-1} [k(x,y) - k'(x,y)]^2}{\sum_{x=0}^{m-1} \sum_{y=0}^{n-1} [k(x,y)]^2} \tag{8}$$

$$SSIM(i,j) = \frac{(2\mu_i\mu_j + c_1)(2\sigma_{ij} + c_2)}{(\mu_{i^2} + \mu_{j^2} + c_1)(\sigma_{i^2} + \sigma_{j^2} + c_2)} \tag{9}$$

Where, i and j are represented as windows in the original k and denoised image k', σ and μ are denoted as standard deviation and mean of i and j, and c_1 and c_2 are represented as constants. The mean of SSIM is denoted in equation (10).

$$MSSIM(k, k') = \frac{1}{W} \sum_{y=1}^{W} (SSIM(i,j)) \tag{10}$$

Where, W is stated as windows in the image.

$$UIQI\ (i,j) = l(i,j) \cdot c(i,j) \cdot s(i,j) = \frac{4\mu_i\mu_j\mu_{ij}}{(\mu_{i^2} + \mu_{j^2})(\sigma_{i^2} + \sigma_{j^2})} \tag{11}$$

Where, $l(i,j) = \frac{2\mu_i\mu_j}{\mu_{i^2}+\mu_{j^2}}$, $c(i,j) = \frac{2\sigma_i\sigma_j}{\sigma_{i^2}+\sigma_{j^2}}$, and $s(i,j) = \frac{2\sigma_{i,j}}{\sigma_i+\sigma_j}$. In that, $\mu_i\mu_j$ is denoted as mean values of original and denoised image, $\sigma_i\sigma_j$ is represented as standard deviation of original and denoised image and σ_{ij} indicates covariance of both original and denoised images. In addition, VIF helps in calculating the distortion or similarity between noisy image k and denoised image k', which is mathematically denoted in equation (12).

$$VIF = \frac{M(k;\ k')}{M(k;h)} \tag{12}$$

Where, h is the image that the human visual system perceives. The mutual information $M(k;\ k')$ and $M(k;h)$ represented as extracted information.

4.3 Data Collection

An extensively applied dataset underwater photography fish is utilized for investigating the performance of modified fuzzy set filter. The undertaken dataset comprises of 1559 different species (parrot-fish, angel-fish, butterfly-fish, etc.) with 8330 images. Generally, the underwater images have poor contrast, so a pre-processing method (contrast enhancement) is preferred for enhancing the quality of images. When contrast enhancement is applied to the noisy images, it resulted in amplifying the noise artifacts. Therefore, contrast enhancement is carried-out on the underwater images, which have low estimated noise. The preferred underwater images for experimental analysis are presented in Figure 5.
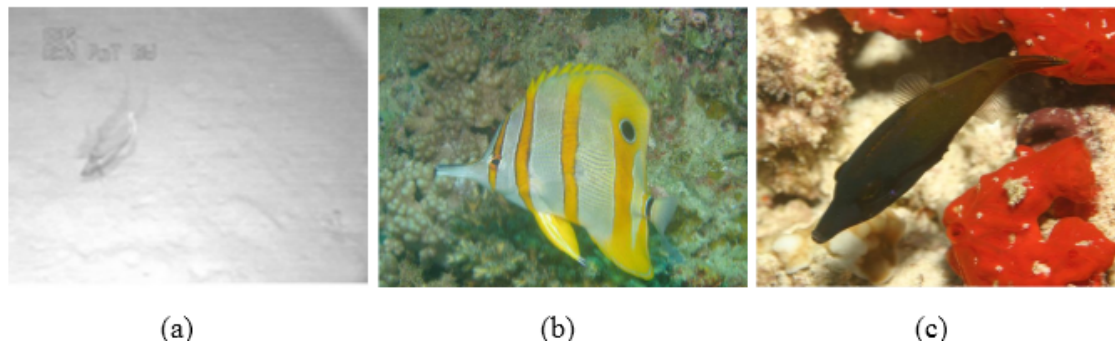
Figure 5: a) Image A with 3.46 *ne* b) Image B with 2.60 *ne* c) Image C with 1.34 *ne*

4.4 Quantitative Analysis

In this sub-section, the underwater photography fish dataset is used to assess the performance of modified fuzzy set filter. In this research, performance evaluation of proposed filter is validated in light of PSNR, MSSIM, SSIM, MSE, UIQI, VIF and NMSE. Here, the performance evaluation is validated for three random underwater images with 0.01, 0.03 and 0.1 level of Gaussian noise. In Table 2, the performance of the modified fuzzy set filter is validated by adding 0.01 level of Gaussian noise in the original underwater images.

Table 2: Performance of modified fuzzy set filter by adding 0.01 level of Gaussian noise

Image	Gaussian noise=0.01 Level						
	PSNR (dB)	NMSE	MSSIM	SSIM	UIQI	MSE	VIF
A	24.94	0.0038	0.3061	0.5135	0.2148	0.0047	0.721
B	22.21	0.0060	0.6552	0.6554	0.3882	0.0060	0.677
C	23.25	0.0046	0.2979	0.7387	0.4068	0.0070	0.7148

The modified fuzzy set filter averagely delivered 23.4667 dB of PSNR, 0.0048 of NMSE value, 0.4197 of MSSIM value, 0.6358 of SSIM value, 0.3366 of UIQI value, 0.0059 of MSE value, and 0.704 of VIF value. In Table 2, image A achieved better results by means of PSNR, NMSE, MSSIM, SSIM, UIQI, MSE, and VIF values (24.94, 0.0038, 0.3061, 0.5135, 0.2148, 0.0047, and 0.721). The noisy image (with 0.01 level of Gaussian noise) and denoised image are denoted in Figure 6.

Additionally, the modified fuzzy set filter is validated by adding 0.03 level of Gaussian noise in the original underwater images, which detailed in Table 3. The modified fuzzy set filter achieved 24.09 dB of PSNR, 0.0040 of NMSE value, 0.3086 of MSSIM value, 0.5109 of SSIM value, 0.2165 of UIQI, 0.00526 of MSE value, and 0.7151 of VIF value for an image A, which showed better result by means of PSNR, NMSE, MSSIM, SSIM, UIQI, MSE, and VIF related to other two images. Similarly, the image B and C achieved 21.83 dB and 22.73 dB of PSNR, 0.0060 and 0.0048 of NMSE value, 0.6510 and 0.2932 of MSSIM value, 0.6559 and 0.7332 of SSIM value, 0.3902 and 0.4047 of UIQI value, 0.0065 and 0.00750 of MSE value, and 0.674 and 0.7136 of VIF value. The noisy image with 0.03 level of Gaussian noise and denoised image are denoted in Figure 7.

In addition, the modified fuzzy set filter is analyzed with higher level of noise (0.1 Gaussian noise level) that is explained in Table 4. In image A, the modified fuzzy set filter attained 18.70 dB of PSNR, 0.0067 of NMSE value, 0.4144 of MSSIM, 0.5025 of SSIM, 0.2122 of UIQI, 0.0134 of MSE, and 0.7305 of VIF. Correspondingly, the images B and C attained 18.32 dB and 18.27 dB of PSNR, 0.0074 and 0.0048 of NMSE value, 0.6374 and 0.3121 of MSSIM value, 0.6415 and 0.7012 of SSIM value, 0.3799 and 0.3922 of UIQI value, 0.0147 and 0.01487 of MSE value, and 0.6693 and 0.72485 of VIF value. The noisy image with 0.1 Gaussian noise level and denoised image are denoted in Figure 8.
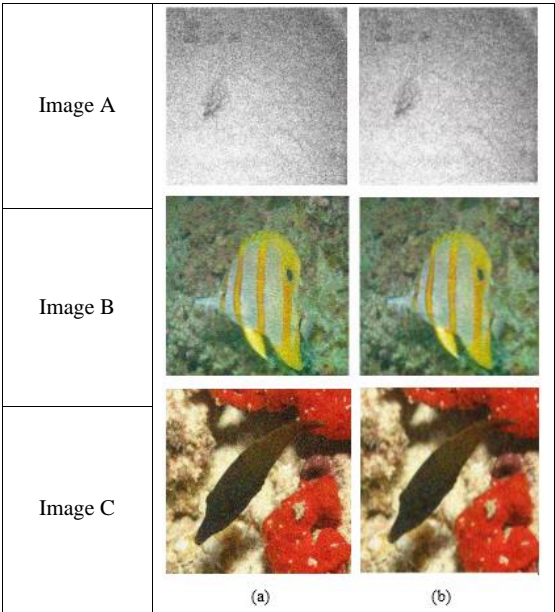
Figure 6: (a) Images with 0.01 Level Gaussian noise, (b) Denoised images

Table 3: Performance of modified fuzzy set filter by adding 0.03 level of Gaussian noise

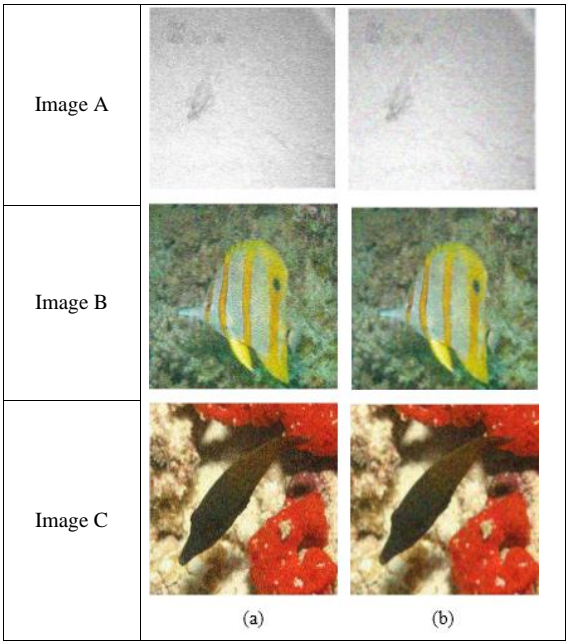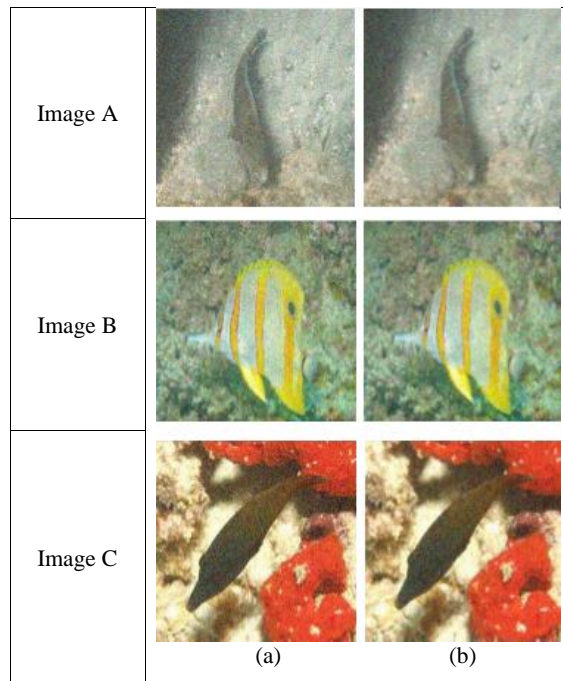| Image	Gaussian noise=0.03 Level						
	PSNR (dB)	**NMSE**	**MSSIM**	**SSIM**	**UIQI**	**MSE**	**VIF**
A	24.09	0.0040	0.3086	0.5109	0.2165	0.00526	0.7151
B	21.83	0.0060	0.6510	0.6559	0.3902	0.0065	0.674
C	22.73	0.0048	0.2932	0.7332	0.4047	0.00750	0.7136

Figure 7: (a) Images with 0.03 Level Gaussian noise, (b) Denoised images

Table 4: Performance of modified fuzzy set filter by adding 0.1 level of Gaussian noise

Image	Gaussian noise=0.1 Level						
	PSNR (dB)	**NMSE**	**MSSIM**	**SSIM**	**UIQI**	**MSE**	**VIF**
A	18.70	0.0067	0.4144	0.5025	0.2122	0.0134	0.7305
B	18.32	0.0074	0.6374	0.6415	0.3799	0.0147	0.6693
C	18.27	0.0048	0.3121	0.7012	0.3922	0.01487	0.72485

Figure 8: (a) Images with 0.1 Level Gaussian noise, (b) Denoised images

4.5 Comparative Analysis

Currently, patch based methodologies are used for image denoising, but these approaches require a lot of edge information and similar image patches, which is limited in underwater images. In this study, a modified fuzzy set filter is proposed for distinguishing the noise and edge of the underwater images. In Table 5, the comparative analysis is done between the modified fuzzy set filter and the traditional filters (mean filter [33], Wiener filter [33], Triangle Fuzzy Filter with Median Center (TMED) [33], Asymmetrical Triangle Fuzzy Filter with Median Center (ATMED) [33], Symmetrical Triangle Fuzzy Filter with Average Center (TMAV) [33], Adaptive Fuzzy filter (AFF) [33], Non-Local Means (NLM) filter, and Weighted Gradient Filter (WGF)). Here, the efficiency of the modified fuzzy set filter is verified by adding Gaussian noise (noise level=0.01, and 0.03). The traditional filters work averagely in the noisy pixels, so it attains average texture information compared to proposed filter.
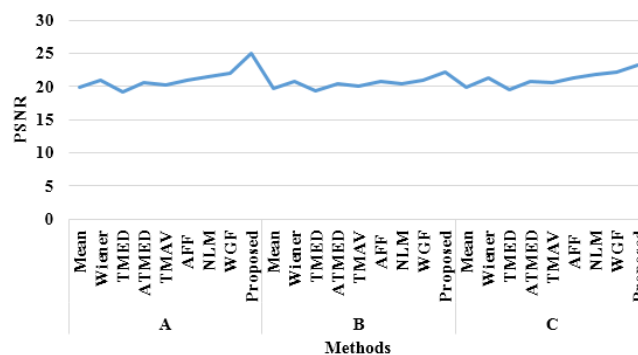
4.5.1 Performance Evaluation using PSNR

In this section, the performance of modified fuzzy set filter and the existing filters (mean filter [33], Wiener filter [33], TMED [33], ATMED [33], TMAV [33], AFF [33], NLM filter and WGF) evaluated by utilizing underwater fish dataset. Here, the proposed and existing filters evaluated by means of PSNR value for both Gaussian noise levels (0.01 and 0.03). In Table 5, the modified fuzzy set filter averagely achieved 23.175 dB of PSNR value and

Table 5: Comparative analysis between modified fuzzy set filter and existing filters

Image	Filters	Gaussian noise=0.01 Level			Gaussian noise=0.03 Level		
		PSNR (dB)	NMSE	MSSIM	PSNR (dB)	NMSE	MSSIM
A	Mean [33]	19.83	0.018	0.64	15.88	0.046	0.55
	Wiener [33]	20.94	0.014	0.54	16.99	0.037	0.48
	TMED [33]	19.10	0.020	0.56	15.15	0.052	0.44
	ATMED [33]	20.64	0.015	0.71	16.49	0.038	0.69
	TMAV [33]	20.22	0.016	0.69	16.21	0.040	0.61
	AFF [33]	20.96	0.013	0.65	16.87	0.035	0.57
	NLM	21.37	0.0072	0.36	20.78	0.011	0.51
	WGF	22.01	0.0061	0.35	21.71	0.0091	0.48
	Proposed	**24.94**	**0.0038**	**0.3061**	**24.09**	**0.0040**	**0.3086**
B	Mean [33]	19.61	0.043	0.74	15.34	0.105	0.62
	Wiener [33]	20.65	0.036	0.70	16.31	0.089	0.58
	TMED [33]	19.28	0.048	0.72	14.92	0.123	0.58
	ATMED [33]	20.33	0.039	0.82	15.85	0.099	0.74
	TMAV [33]	20.07	0.040	0.80	15.68	0.104	0.71
	AFF [33]	20.68	0.032	0.77	16.25	0.091	0.66
	NLM	20.39	0.0072	0.68	17.73	0.071	0.67
	WGF	20.99	0.0069	0.66	19.09	0.021	0.66
	Proposed	**22.21**	**0.0060**	**0.6552**	**21.83**	**0.0060**	**0.6510**
C	Mean [33]	19.90	0.035	0.58	16.01	0.085	0.39
	Wiener [33]	21.22	0.029	0.69	17.07	0.062	0.59
	TMED [33]	19.57	0.039	0.68	15.32	0.102	0.52
	ATMED [33]	20.82	0.029	0.82	16.63	0.075	0.76
	TMAV [33]	20.51	0.032	0.79	16.36	0.080	0.69
	AFF [33]	21.22	0.026	0.77	17.09	0.068	0.67
	NLM	21.76	0.015	0.41	18.76	0.069	0.68
	WGF	22.14	0.0082	0.39	20.55	0.057	0.52
	Proposed	**23.25**	**0.0046**	**0.2979**	**22.73**	**0.0048**	**0.2932**

the traditional filters mean filter, Wiener filter, TMED, ATMED, TMAV, AFF, NLM filter and WGF delivered 17.76 dB, 18.863 dB, 17.22 dB, 18.46 dB, 18.175 dB, 18.845 dB, 20.13 dB, and 21.08 dB. Graphical comparison of PSNR value for both existing and proposed filter is denoted in the Figures 9 and 10.

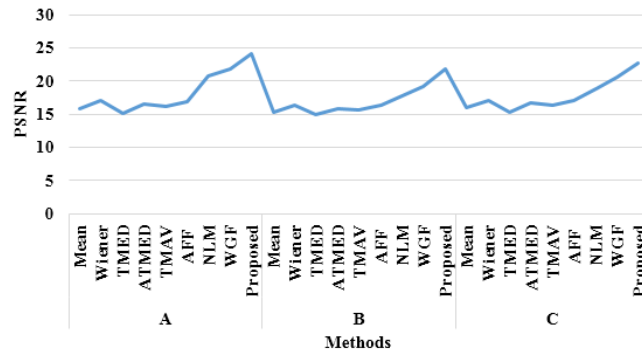**Figure 9:** Graphical comparison of PSNR value (0.01 Level Gaussian noise)

Figure 10: Graphical comparison of PSNR value (0.03 Level Gaussian noise)

4.5.2 Performance Evaluation using NMSE

Inspecting the Table 5, the modified fuzzy set filter outperformed with higher NMSE value of 0.0038 in an image A as compared to the traditional filters such as mean filter [33], Wiener filter [33], TMED [33], ATMED [33], TMAV [33], AFF [33], NLM filter and WGF. The existing filters achieved minimum NMSE value, compared to modified fuzzy set filter. The graphical comparison of NMSE value for both existing and proposed filter is indicated in Figure 11.
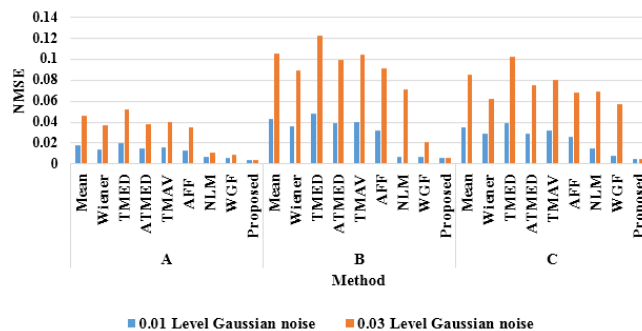

Figure 11: Graphical comparison of NMSE value (0.01 and 0.03 Level Gaussian noise)

4.5.3 Performance Evaluation using MSSIM

In this experimental research, the validation outcome is carried out in two phases such as adding Gaussian with 0.01 and adding Gaussian with 0.03. The average MSSIM value of modified fuzzy set filter achieved 0.4186 and the existing filters (mean filter [33], Wiener filter [33], TMED [33], ATMED [33], TMAV [33], AFF [33], NLM filter and WGF), which delivers 0.5867, 0.5967. 0.5834, 0.7567, 0.715, 0.68167, 0.55167, and 0.51 of average MSSIM values. The graphical comparison of MSSIM value for existing and proposed filter is represented in Figure 12. The experimental outcome of the overall results stated that modified fuzzy set filter worked effectively in underwater images compared to other traditional filters. Also, it is identified that the modified fuzzy set filter able to perform both visually and subjectively.
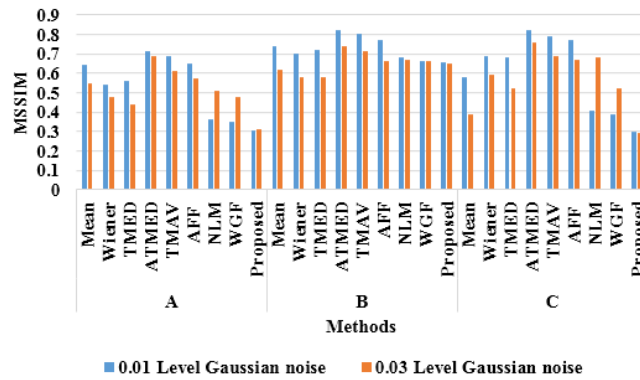
Figure 12: Graphical comparison of MSSIM value (0.01 and 0.03 Level Gaussian noise)

4.5.4 Discussion

During the transmission and acquisition processes, noise is introduced in the digital images that effectively degrades the quality of images. Therefore, an accurate recognition of noise level helps in improving the quality of images that is crucial in several real time applications like image retrieval, object detection, video surveillance, biometric authentication, etc. In this research, modified fuzzy set filter is proposed to retain edge information and also to remove noise for restoring the digital image. The efficacy of the modified fuzzy set filter is shown in Table 5. The performance investigation is done by utilizing the performance metrics like PSNR, MSSIM, SSIM, MSE, UIQI and NMSE. Under different Gaussian noise levels, the performance of the proposed and existing filters are validated. From the experimental simulation, modified fuzzy set filter showed 2-3 dB enhancement in PSNR, 0.12-0.03 improvement in MSSIM value and 0.38-0.1 enhancement in NMSE value compared to the prior filtering methods like mean filter, Wiener filter, TMED, ATMED, TMAV, AFF, NLM filter and WGF. A few key benefits of modified fuzzy set filter are conceptually simple, more robust against Gaussian noise and effectively preserves the fine structure of the image.

5 Conclusion

In digital image processing, the noisy digital images are harnessed to the intended operations, specifically when the noise level is too high. To address this issue, many image denoising schemes are developed in several applications like medical image analysis, biometric authentication, pattern recognition etc. for reducing the noise level in a digital image. In this research paper, modified fuzzy set filter is proposed based on the objectives for improving the robustness and imperceptibility of underwater images. At first, the modified fuzzy set filter was applied to the lower estimated underwater noise images. For checking the dynamic characteristics of modified fuzzy set filter, various Gaussian noise levels are simulated on the underwater images and results are evaluated. Related to other existing schemes, the modified fuzzy set filter delivers an effective performance by means of PSNR, MSSIM, SSIM, MSE, UIQI and NMSE. The modified fuzzy set filter almost achieved 2-3 dB enhancement in PSNR, 0.12-0.03 improvement in MSSIM value and 0.38-0.1 enhancement in NMSE value compared to the prior methods. In future work, an efficient optimization algorithm will be utilized to optimize the fuzzy rules for further improving the denoising performance.

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