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An Optimal Filter Selection on Grey Scale Image for De-Noising by using Fuzzy Technique

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Abstract: Images are helpful in applications like denoising, computer vision, and pattern recognition. The poor-quality images impacts image quality enhancement and assessment. For enhancing images, denoising techniques are utilized to improve the quality of the image. In denoising process, the algorithm's running time and preservation of visual features are significant issues. However several recent contributions exist, but efficiency is a crucial issue with those techniques. Therefore, the current paper proposes an adaptive decision filter selection technique, which selects the optimal Laplacian operator. The utilization of appropriate operators improves image quality and reduces the overhead of repetitive operator selection-based techniques. An Adoptive Image Quality Feedback (AIQF) has been involved, which is used to select the optimal filter based on noise availability and consequently, it guarantees optimal image quality. The simulation on MATLAB has been carried out with the publically available datasets. The experimental results indicate that AIQF based technique outperforms similar noise removal techniques. Thus, the AIQF-based technique has been compared with similar algorithms. The peak signal-to-noise ratio (PSNR), structural similarity (SSIM) matrix and Mean square error (MSE) are used for performance evaluation. Based on the comparison, the proposed technique reduces denoising time and demonstrates the superiority of the proposed AIQF-based methods.

Keywords: *Image Denoising, Decision Making, Image Quality, Impulse Noise, Salt and Pepper Noise.*

1. Introduction

The new communication and information technology enable the applications of machine learning and artificial intelligence. In these technologies, heterogeneous data types have been utilized to serve these applications. Sometimes this data has been used for critical and situational decision-making [1]. In such applications, digital images also play a significant role in knowledge extraction and other tasks. In digital images, the quality of images is a critical concern. The quality of images can be affected during the capturing of images due to different kinds of noise [2]. Therefore, the noise filtering technique has an essential role in image-based applications. In this presented study, the image denoising technique of images has been proposed.

However there are several image-denoising techniques available, but some are inefficient or have significant computational complexity. Therefore these algorithms are not much suitable for real-time applications as compare to current research [3]. Image denoising is a mechanism to remove or minimize the number of corrupted pixels which are influenced due to noise. The color image denoising and grayscale image denoising are different because, in color image denoising, it is relatively essential to consider the color channels individually [4]. However, determining the best collection of pixels to replace the damaged pixels during operations is necessary for the image denoising process. In this context, pixel replacement techniques utilize filters (i.e., Mean, Median, etc.) [5]. The different filters are characterized differently, and also these filters can process the image pixels differently. Therefore, optimal filter

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selection also has essential criteria for image denoising [6]. Consequently, the proposed work aims to design a self-adaptive decision-making function for selecting an optimal denoising filter for image quality enhancement. The current proposed work involves the denoising filter selection method with recent noteworthy contributions in image denoising. The literature summary has been done in accordance with research problems, methods used, and consequences.

Further, a proposed technique of denoising the filter selection method for design and implementation has been used. An extensive experimental study has been carried out, and a comparative performance study has been reported. Finally, the entire effort has been made on experiments, findings, and future directions.

2. Backgrounds

The recently contributed research work has been initially collected to find the domain of the proposed work. The section is composed of the two sub-sections such as:

2.1 Keywords

Table 1. Frequently used keywords

Term	Full Form	Term	Full Form
NLM	Nonlocal Mean	PSNR	Peak Signal to Noise Ratio
MSE	Mean Square Error	RGB	Red, Green, and Blue
JDD	Joint Demo-saicking and Denoising	MC	Multi-Channel
MCWSNM	Multi-Channel Weighted Schatten p-Norm Minimization	WTNN	Weighted Tensor Nuclear Norm
LRQA	Low-Rank Quaternion Approximation	SAID-END	Spatially Adaptive Denoising via Enhanced Noise Detection
QNLTV	Quaternion Non-local Total Variation	FM-NLM	NLM Algorithm with Fuzzy Metric
FCM	Fuzzy C Means	FSVM	Fuzzy-Support Vector Machine
QANLCM	Quaternion Adaptive Nonlocal Coupled Means	SVM	Support Vector Machine
KH	Krill Herd	PSO	Particle Swarm Optimization
FIS	Fuzzy Inference System		

2.2 Related Work and Literature Survey

An MC optimization for picture denoising is proposed by Xu et al. RGB patches are merged with each other and introduce a weight matrix [7]. Formulation has been done with the linear equality-constrained problem and solves it using alternating directions. Kong et al. use a block diagonal matrix formulation to examine the potential and significance of patch level [8]. A straightforward transform-threshold-inverse method is constructed using principal component analysis and a global patch for compatible findings is used with rapid execution. Helou et al. propose a blind and universal deep-learning image denoiser based on optimal denoising and call fusion [9]. The Gaussian prior assumption serves as the basis for the research. It can withstand the noise levels that are invisible. Huang et al. propose the MCWSNM model with similar vectorized cubic patches have been analyzed and clustered to build a less-rank matrix for a local RGB patch in a noisy image [10].

Similarly, Sadreazami et al. employ identical nonlocal patches of each channel and group them to form a block with sparse coding that can reduce high-frequency noise [11]. Then, a technique based on iterative graph filtering is suggested. A nonlocal and inter-channel dependency-aware prior dubbed the WTNN is proposed by Hosono et al.[12]. When applied to tensors having non-locally comparable patches, the WTNN acts as a patch tensor. Chen et al. propose an LRQA using two components: color image pixel and LRMA-based method, and encoded as a quaternion matrix. As a second point, LRQA includes the low-rank constraint [13]. A SAID-END technique is developed for color and grayscale images by Singh et al. [14]. This is accomplished by a two-stage strategy that includes non-corrupted pixel-sensitive adaptive image enhancement and adaptive noise recognition. The technique is used to ensure its versatility and robustness.

Table 2. Review Summary

Ref.	Issue	Solution	Methods	Results
[7]	Extension of grayscale to denoising is complex due to noise level in R, G, and B channels	Framework for multi-channel weighted nuclear norm minimization.	RGB patches for channel redundancy and balance data fidelity. Linear equality-constrained using alternating direction.	PSNR (natural Image) = 29.31dB, PSNR (real Image) = 37.71dB. Time =202.9 MS
[8]	Filtering images of more than one channel.	Examine the potential and influence of patch level.	Global patches, with PCA in the clustering, a transform-threshold-inverse technique.	Confirm its durability, efficacy, and efficiency.

[9]	Blind and universal image denoising for any noise level	The elimination of Gaussian noise from images using deep learning.	An ideal denoising method using the Gaussian prior assumption is called fusion denoising.	Strength to unseen noise. Improve image by 0.1dB.
[10]	R, G, and B channels have different noise statistics.	Multi-Channel Weighted Schatten p-Norm Minimization - MCWSNM	Use small patches, to find similar patches. Vectorized to construct low-rank matrix and solved via alternating direction.	On real color image CC Dataset avg PSNR 38.98 dB.
[11]	Graph signal processing innovations inspired this study.	Nonlocal alike patches of every color are clustered into a block for a graph-based outline.	Graph-based sparse coding can remove high noise. Improve contrast by graph filtering.	PSNR for Noise 10 = 35.53, 20 = 31.94, 30 = 29.90, 40 = 28.73 dB
[12]	Low rankness prior can effect on performance. Methods have channel dependency so the de-noised image has artifacts.	An inter-channel dependency-aware prior and nonlocal are called the WTNN.	Adding a prerequisite to NLSS Tensors with non-locally identical patches can benefit from WTNN, as it is a low-rankness, third-order patch tensor.	Avg. PSNR for 20% noise 31.83, 50% noise 27.51
[13]	LRMA methods with color images not use correlation.	LRQA model.	Scalar representation, LRMA, encoding; LRQA imposes the low-rank constraint.	PSNR noise 50% = 28.96, 75% = 24.70, 85% =22.83
[14]	Low performances in heavy noise and over/under detection are two drawbacks.	SAID-END	The first stage, known as enhanced adaptive noise detection, is followed by the second stage, known as non-corrupted pixel sensitive adaptive picture restoration.	Mean PSNR for noise up to 90% = 35.35 dB, and SSIM = 0.93
[15]	Models fail for textures and disturbing visuals. Deep learning has high cost.	A weightless convolutional neural network for JDD problem.	Dense network to learn mapping. Aggregated transformation and deep residue learning of sparsity models.	Demosaicking-only PSNR= 45.51, SSIM = 0.99, JDD PSNR= 34.88, SSIM= 0.93

3. Proposed Work

The proposed work aims to make an effort to improve the existing image-denoising method. The color image denoising filter is considered to enhance their performance. Additionally, simulation has been done on grayscale images for denoising. It is essential because noisy images may deliver incomplete information, which can impact the application's quality of Service (QoS). However, a number of techniques are available for image denoising, but most of them are less efficient and unable to deal with a higher level of noise. In addition, some techniques are not able to preserve the image features like texture and edges. In this paper, two noteworthy methods which are promising for effective image denoising have been identified. The proposed solution is derived from these two denoising solutions. Both solutions are based on fuzzy decision filters and provide solutions for color image denoising. In this work, some modifications have been made to apply it to the grayscale image. The Adoptive Image Quality Feedback (AIQF) as a decision-making process for selecting the optimal denoising filter. The selection of filters ensures the optimal image visual quality.

According to the modified switching median filter (MSMF), H ×W× 3 denotes a color image, which is a 2D array. Here, 3 stands for three vectors of color channels (R, G, and B). The pixels vary between 0 to 255, let $p_k(i-L, j-L), \ldots, p_k(i, j), \ldots, p_k(i+L, j+L)$ shows part of image for a window (2L + 1)(2L + 1); $p_k(i, j)$ is the present pixel of image; The value N represents the total number of pixels. $\left\{x_{1k}, x_{2k}, \ldots, x_{(\frac{N+1}{2})k}, \ldots, x_{Nk}\right\}$ is the findings of a sliding window. Initially, AVMF is used to find out corrupted pixels. $\frac{1}{r}\sum_{m=1}^{r} x_{mk}$ is the average of r pixels just before to x_{rk} in $\left\{x_{1k}, x_{2k}, \ldots, x_{(\frac{N+1}{2})k}, \ldots, x_{1Nk}\right\}$.

$$\left\|\frac{1}{r}\sum_{m=1}^{r} x_{mk} - p_k(i,j)\right\|_2 \succ Tol \quad (1)$$

For noise pixel $p_k(i, j)$, use four Laplacian operators to detect noise. The four convolution kernels are $w_p\,(p = 1-4)$ correspondingly. By using equations (2) and (3) minimum difference of convolutions z_{ij} is applicable for the detection of edges.

$$z_{ij} = min\{p_k(i,j) \otimes w_p | : p = 1 - 4\} \quad (2)$$

$$y^{MSMF} = \{^{y^{VMF}}_{p_{k(i,j)}} z_{ij} \geq T_{otherwise}\} \quad (3)$$

The information loss and image details are one of the most crucial. So, in MSMF center pixel is classified as noisy or edge. If the pixel is an edge, no changes are made to it. Further, the noisy pixel was detected on the basis of a threshold. However, defining a threshold is complex due to the ambiguity and uncertainty of impulse noise. As a result, by altering the MSMF, a fuzzy decision vector filter (FDF) is created. Here, noise detection is accomplished using fuzzy membership. Fuzzy [16] membership is given by equations (4) and (5). A soft threshold is used to use additional evidence than a binary choice. For noise, it calculates the memberships. $d_{\max}$ is the maximum difference among two pixels, and $d_{\min}$ is the minimum difference:

$$Z_{ij} = \begin{cases} d_{\max} & z_{ij} \succ d_{\max} \\ z_{ij} & otherwise \end{cases} \quad (4)$$

$$\mu(i,j) = \frac{dij_{max}}{dmin_{max}} \quad (5)$$

In Eq. (4), the pixel will be categorized as noisy and noise-free. Then calculate the restored image using Eq. (5). If $(i,j) \geq 0.9$, then the pixel is measured as noise-free and kept constant. Else, it represents noise. Thus, we replace the central pixel with the help of averaging the pixels that $(i+u, j+v) \geq 0.8$. Whenever any of the pixels doesn't satisfy $(i+u, j+v) \geq 0.8$, the central pixel takes place with the mean of pixels that satisfy $0.8 \geq (i+u, j+v) \geq 0.6$.These constraints are defined using equation (6).The technique preserves the benefits of the switching vector filter while enhancing pixel categorization accuracy. In addition, eliminating Gaussian noise can be accomplished by combining FDF with NLM.

$$y^{FDF} = \left\{ \begin{array}{ll} p_k(i,j) & if\ \mu(i,j) \geq 0.9 \\ \dfrac{p_k(i+u, j+v)\mu(i+u, j+v)}{\sum_{u \in N, v \in N} \mu(i+u, j+v)} & if\ \mu(i,j) \leq 0.9\ and\ \mu(i+u, j+v) \geq 0.8 \\ \dfrac{p_k(i+u, j+v)\mu(i+u, j+v)}{\sum_{u \in N, v \in N} \mu(i+u, j+v)} & otherwise (0.8 \geq (i+u, j+v) \geq 0.6), otherwise \end{array} \right\} \quad (6)$$

The idea of the proposed image denoising filter has been taken from the FDF[18,19] and NLM methods. The proposed model's step process is given in figure 1.

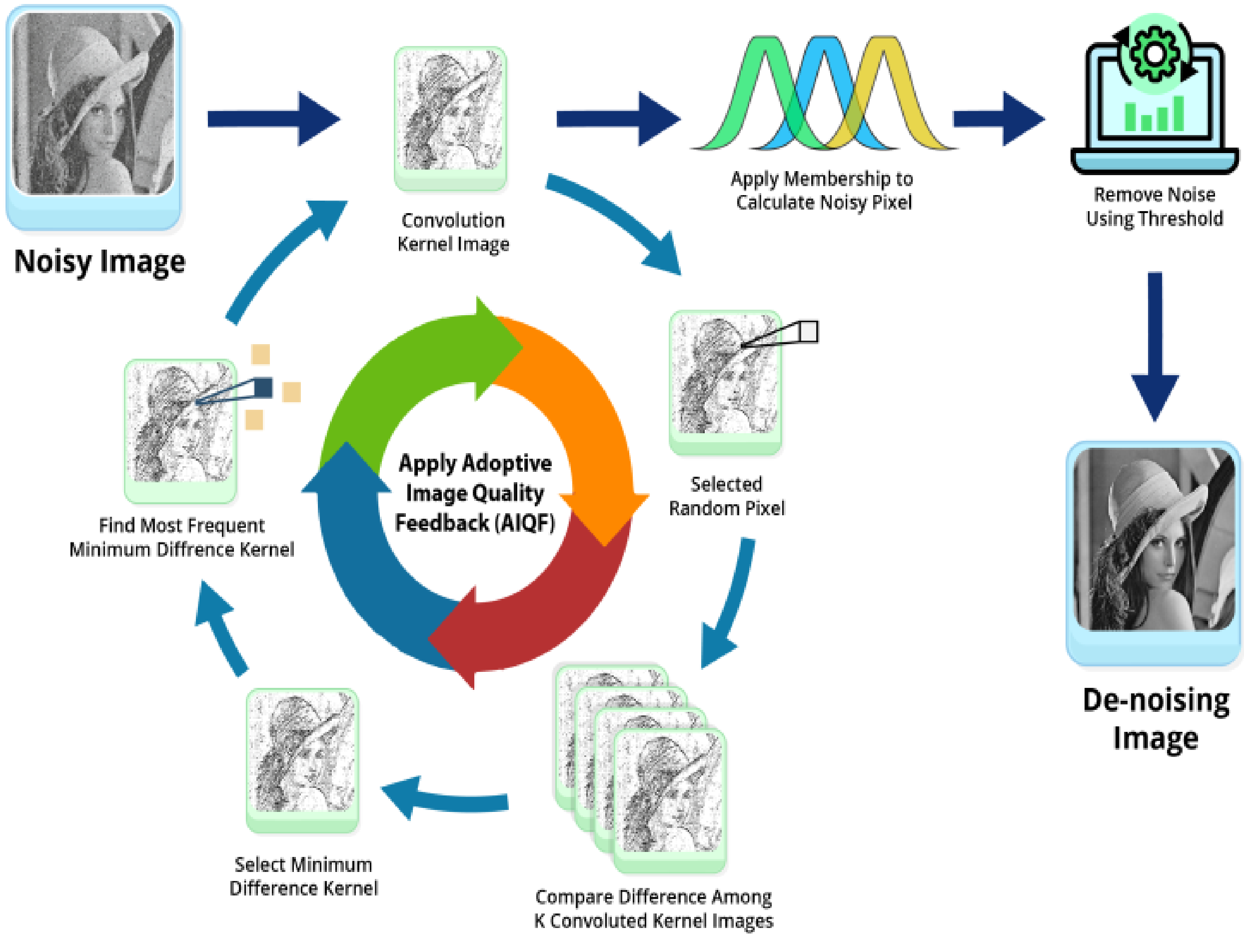


Fig.1 Proposed AIQF model

According to the given model in figure 1, the system accepts the noisy image. The input image is a grayscaled image and can be expressed using two-dimensional vectors of M rows and N columns such that M X N. Gaussian noise corrupts the image (Salt and Pepper). A noisy image is pre- processed to extract the image histogram. By using the histogram, the image is analyzed to understand the noise distribution. Further, an Adoptive Image Quality Feed Back (AIQF). Technique has been applied to find the optimal Laplacian operator for the given image. The four Laplacian operators are demonstrated in figure 2:

0	0	0	0	0
0	0	0	0	0
-1	-1	4	-1	-1
0	0	0	0	0
0	0	0	0	0

Operator A

0	0	-1	0	0
0	0	-1	0	0
0	0	4	0	0
0	0	-1	0	0
0	0	-1	0	0

Operator B

-1	0	0	0	0
0	-1	0	0	0
0	0	4	0	0
0	0	0	-1	0
0	0	0	0	-1

Operator C

0	0	0	0	-1
0	0	0	-1	0
0	0	4	0	0
0	-1	0	0	0
-1	0	0	0	0

Operator D

Fig. 2 Four Laplacian operators

3.1 Adoptive Image Quality Feed Back (AIQF)

Now we suppose that at a noisy image at location (i, j) the pixel is $p_k(i, j)$. Pixel is used with four Laplacian operators. These operators are used to differentiate among edge or noise pixels, which is a time-consuming process. Because each image pixel $p_k(i, j)$ is convolved with four convolution kernels $w_p(p=1-4)$. Edge detection is accomplished by finding the z_{ij}, with a minor difference among these four convolutions. Therefore, we proposed an AIQF model for selecting the optimal convolution kernel. Using this AIQF model, an effort has been made to reduce the convolutional time. Therefore, the selection of k random pixels has been done from the entire image, where k > 1 and k is a real odd number. After this, equation (7) has been utilized for convolution with all four kernels.

$$z_{ij} = min\{ p_k(i,j) \otimes w_p |: p = 1 - 4\} \quad (7)$$

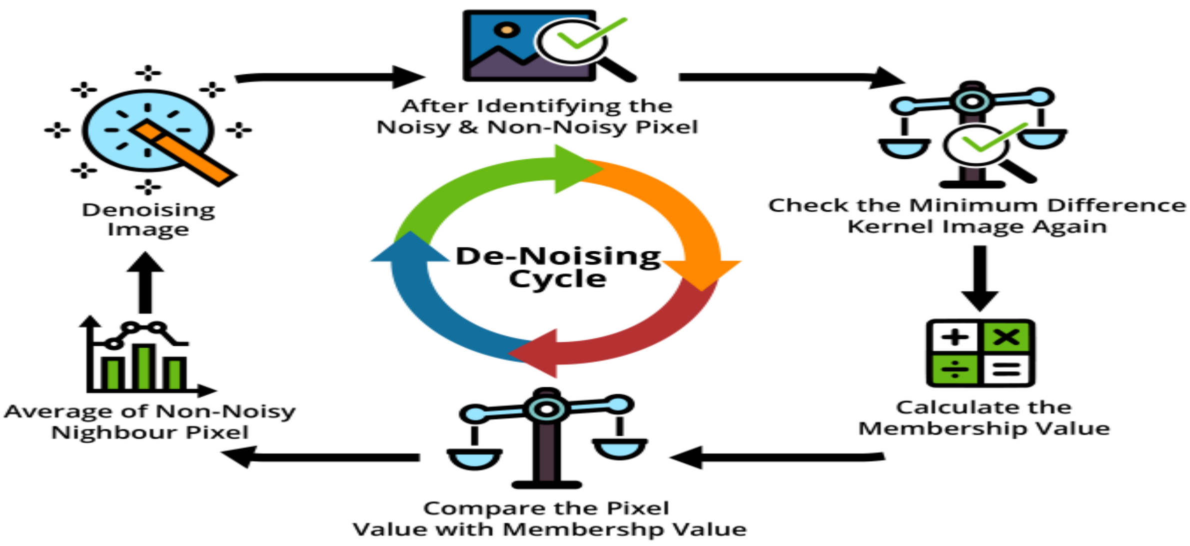


Fig. 3 Procedure of the hybrid AIQF model using fuzzy membership

Equation (7) returns the kernel with a minimum difference for each k-selected pixel. Now, [17] select the most frequent filter in the k samples. Thus the most frequent kernel is suggested as the optimal filter. At last for filtering the entire image optimal kernel has been used for the process. The mean frequency of the filter used is calculated on the basis of the suitable classified pixels. and denoted by equation (8). The higher mf value demonstrates the most frequently used filter. To utilize the optimal kernel ^{Opt}, we modify equation (7) as shown in as shown in equation (9):

$$mf = \frac{1}{N}\sum_{i=1}^{N} w_p(p_k)_i \quad (8)$$

$$D_{ij} = p_k(i,j) \otimes Opt \quad (9)$$

3.2 Noisy Pixel Classification and Denoising

Now to classify the noisy pixel, the concept of soft threshold has been utilized as defined in equation (4) and (5). These two equations are slightly modified to adopt the AIQF model. Thus these two functions are redefined as:

$$D_{ij} = \begin{cases} d_{\max} & D_{ij} \succ d_{\max} \\ D_{ij} & otherwise \end{cases} \quad (10)$$

$$\mu(i,j) = \frac{dij_{max}}{dmin_{max}} \quad (11)$$

Finally, we utilize equation (6) to replace the identified noisy pixels. The consequence of image denoising is demonstrated in table 3. The table consists of the image corrupted by the different noise levels. Additionally, the de-noised images for the noisy images are also given by the proposed filtering model.

In this part, the experimental analysis has been done for the proposed image-denoising technique and the two classical grayscale image-denoising models. The efficiency and performance of these models for image denoising is investigated on three popular image quality matrixes: Peak Signal to Noise Ratio (PSNR) and structural similarity index measure (SSIM). The MSE indicates the cumulative squared error among the original and de-noised image. Equation (12) can be used for this purpose.

$$MSE = \frac{\sum_{M,N}[I_1(m,n) - I_2(M,N)]^2}{M*N} \quad (12)$$

Table 3. Performance of implemented three techniques of color image denoising with the different datasets

Data-set	Noise	10			20			30			40			50		
		AIQF	PCA	FDNLM	AIQF	PCA	FDNLM	AIQF	PCA	FDNLM	AIQF	PCA	FDNLM	AIQF	PCA	FDNLM
D1	PSNR	59.128	29.238	30.25	57.107	25.483	24.433	55.615	23.439	23.148	54.606	22.114	20.129	53.716	21.133	21.589
	SSIM	0.0360	0.7102	0.548	0.1730	0.5561	0.3062	0.0121	0.4520	0.2760	0.022	0.3887	0.2961	-0.0113	0.2443	0.3958
	MSE	0.0705	77.491	78.321	0.1266	183.98	234.25	0.1785	294.56	314.97	0.2251	399.63	631.12	0.2763	500.87	450.96
D2	PSNR	59.503	28.213	31.803	57.284	23.851	27.805	55.781	22.061	25.911	54.634	21.046	24.057	53.803	20.349	22.855
	SSIM	0.0165	0.8677	0.5740	-6288	0.6185	0.4546	-0.004	0.3578	0.3514	-0.017	0.2446	0.2850	-0.012	0.1921	0.1434
	MSE	0.0729	98.122	42.925	0.1215	267.88	107.77	0.1717	404.55	166.70	0.2237	511.06	255.49	0.2708	599.98	336.95
D3	PSNR	58.874	31.613	28.071	56.610	27.805	30.624	55.275	25.911	26.318	54.285	24.057	24.132	53.518	22.855	22.526
	SSIM	0.0685	0.6352	0.4225	0.0165	0.4546	0.6741	0.0076	0.3514	0.4317	-0.005	0.2850	0.3751	0.0044	0.1434	0.2741
	MSE	0.2892	44.842	101.37	0.0843	107.77	56.321	0.1419	166.70	151.77	0.1930	255.49	251.09	0.2424	336.95	363.43
D4	PSNR	58.759	30.624	26.080	56.731	26.318	22.280	55.448	24.132	21.079	54.448	22.526	21.589	53.552	21.282	20.129
	SSIM	0.0396	0.6741	0.3531	0.0261	0.4317	0.4749	0.0117	0.3751	0.3751	7e-06	0.2741	0.3958	-0.0082	0.2334	0.2961
	MSE	0.0865	56.321	160.32	0.138	151.77	384.62	0.1843	251.09	507.18	0.2335	363.43	450.96	0.2870	484.00	631.12

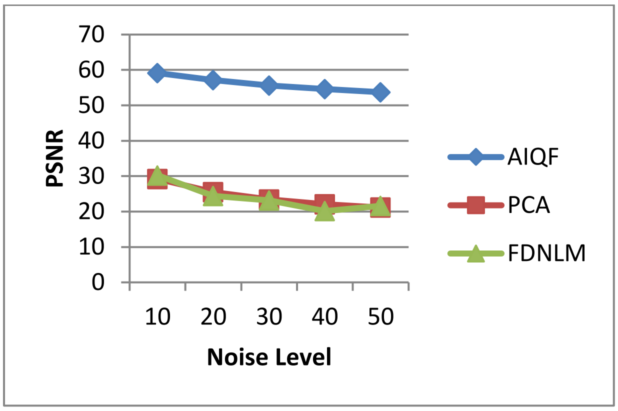
D1 = Lena, D2 = Mandrill, D3 = Women, D4 = Camera man

Whereas PSNR signifies a measure of the peak error and can be defined by equation (13)

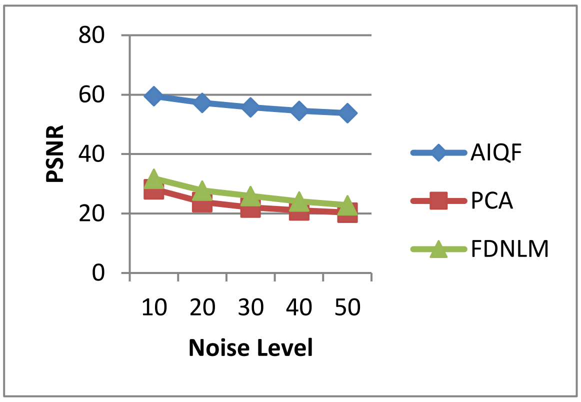
$$PSNR = 10\, log_{10}\left(\frac{R^2}{MSE}\right) \quad (13)$$

Where M and N is the number of rows and columns, respectively, R is the maximum fluctuation in image data, in the case of image, R is 255.

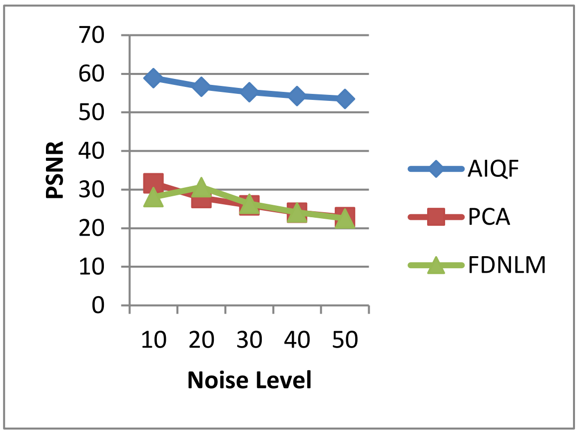
The experiments have been carried out with the publically available datasets, namely, Lena, Mandrill, Women, and Cameraman. The dataset images are corrupted with salt and paper noise and different noise levels, i.e., 10, 20, 30, 40, and 50 percent (%). Additionally, to compare the proposed AIQF



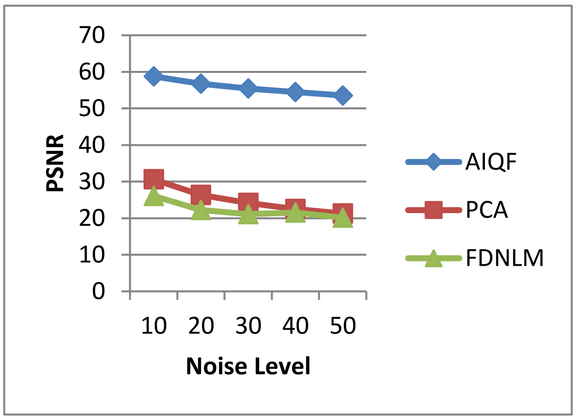
(A)



(B)



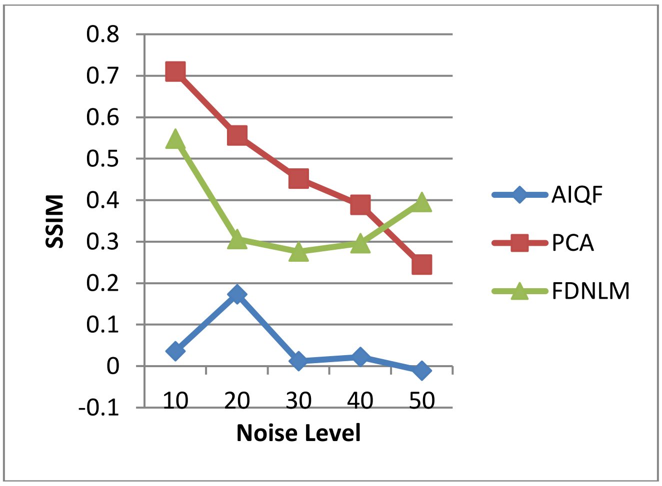
(C)



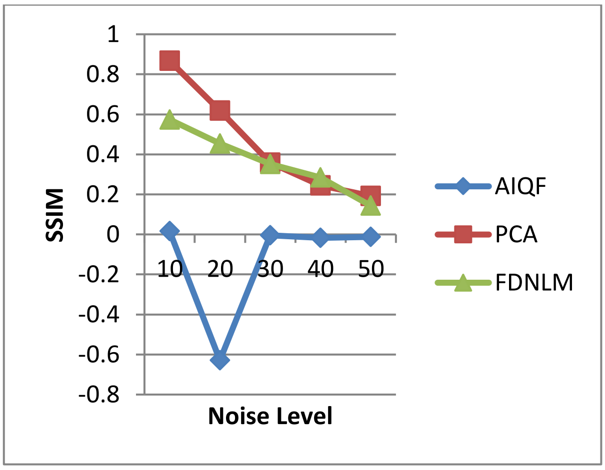
(D)

Fig. 5 Demonstrate comparative performance in terms PSNR for the datasets Lena, (A) Mandrill (B) Women (C) and Camera man (D)

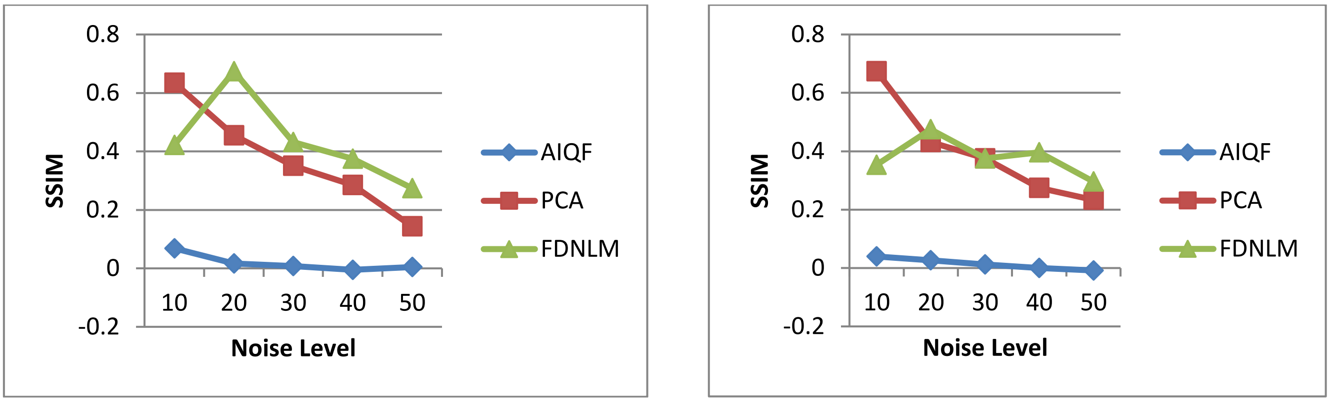
technique, the Fuzzy Decision Non-Local Means (FDNLM) and Principle Component of Analysis (PCA) based denoising has been considered[20,12]. The PSNR of all three techniques are measured and demonstrated in figure 5 and table 3. Figure 5(A-D), show the results of Lena, Mandrill, Women and Camera Men's image. According to the results, we found that the AIQF provides a higher PSNR.



(A)



(B)



(C) (D)

Fig. 6 Demonstrate performance of image denoising techniques in Terms of SSIM for the datasets (A) Lena, (B) Mandrill (C) Women (D) Camera man

Next, we measured SSIM. It is employed to assess how structurally similar two images are. The SSIM of two images x and y of similar size $N \times N$ is represented by equation (14).

$$SSIM = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu^2{}_x + \mu^2{}_y + c_1)(\sigma^2{}_x + \sigma^2{}_y + c_2)} \quad (14)$$

Where, μ_y is the mean of y, μ_x is the mean of x, $\sigma^2{}_y$ is the variance of y, $\sigma^2{}_x$ is the variance of x, σ_{xy} is the covariance of x and y, $c_1 = (k_1, L)^2$, $c_2 = (k_2, L)^2$. Using two variables, the division with a weak denominator can be stabilized, L the dynamic range of the pixel-values, and finally $k_1 = 0.01$ and $k_2 = 0.03$ by default.

Basically, it is the comparison of two images. The SSIM near the 0 is considered a good quality of the resultant image and low information loss. The comparative SSIM of implemented methods has been described in figure 6.Figure 6(A) shows the SSIM of the Lena Image, Figure 6 (B) for Mandrill, Figure 6(C) for Women, and Figure 6(D) shows the SSIM for Camera Man. The result demonstrates the AIQF method provides the SSIM relevant to 0. On the other hand, two other implemented techniques provide higher SSIM. But the noticeable point is that both methods have enhanced their performance with the higher level of noise, but the proposed technique provides consistently improved performance. Thus the AIQF is superior to the other two models.

5. Conclusion

The primary agenda of the planned work is to explore image denoising and contribute it with an enhanced technique. The image-denoising techniques are expensive in terms of computational resources, which needed attention because, in the current scenario, processing images at high speed has been meeting the application's requirements. Image quality also influences the Quality of Service (QoS). Thus, in order to improve two effective approaches for enhancing the speed of filtering by introducing an optimal filter selection method. By selecting the optimal kernel, the enhancement in the superiority of the image, preservation of image features, and enhancement in the algorithm's running time have been easily done. Initially, some samples have been picked, and find the rank kernels. The AIQF-based technique suggests the most appropriate filter. After that, classification is done, and pixels are restored according to the previous technique.The experiments have been carried out on the basis of simulation developed in MATLAB. Additionally, it has been tested the AIQF model by using publically available datasets. Further, the AIQF-based method is compared with two similar image-denoising models. In order to compare the results, MSE, PSNR, and SSIM are considered. Based on obtained results, it has been observed that the proposed AIQF-based model is superior to the other two denoising models. The proposed image denoising is efficient and accurately de-noises the gray images. It has been observed that the various exciting direction of research can be opened in the future as follows:

1. Adopt this technique for color image denoising.
2. Deep learning techniques [18] are also utilized in image denoising.

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