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A HYBRID SVD-DIRECTIONAL FILTERING APPROACH FOR HIGH-DENSITY SALT-AND-PEPPER NOISE REMOVAL FROM GRAYSCALE IMAGES

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ABSTRACT

One of the fundamental challenges in image processing is denoising grayscale images affected by high-density salt-and-pepper noise, where existing median, adaptive, and wavelet-based filters often fail to preserve fine details and structure at noise levels above 70%. To address this gap, this study presents a novel hybrid denoising approach that combines directional filtering with singular value decomposition (SVD). The proposed method leverages directional filtering to preserve edge and textural features while SVD-based reconstruction reduces residual noise through adaptive low-rank approximation. This combination introduces a robust solution for grayscale image denoising at extreme noise densities. Experimental results demonstrate significant improvements in PSNR and SSIM over conventional techniques, providing new knowledge on the effectiveness of hybrid filtering-decomposition methods for image restoration tasks, particularly in scenarios where edge preservation and structural integrity are critical.

Keywords: *Salt and Pepper Noise, Image Denoising, Image restoration, Singular Value Decomposition, Directional Filter*

1. INTRODUCTION

Digital images, processed and stored in pixels, serve as vital visual representations in fields such as science, medicine, remote sensing, and media [1][2]. The quality of these images is critical for tasks ranging from diagnosis to automated inspection. However, noise introduced during image acquisition, compression, or transmission can significantly degrade image quality and impair further processing. Among various noise types, salt-and-pepper noise manifesting as random black and white pixels—presents a particularly challenging problem, especially at high noise densities [3]. This type of impulse noise corrupts pixel information and distorts local image statistics, compromising edge details and structural integrity that are vital in applications like medical imaging and satellite data analysis [4]. Image filtering is an essential pre-processing step for improving image quality by suppressing noise and enhancing features [5][6]. A wide range of denoising techniques have been proposed to address salt-and-pepper noise. Median filters and their variants [7][8] are popular for their simplicity and edge-preserving properties at low noise levels. However, they typically fail at higher noise densities (above 70%), leading to excessive smoothing and loss of fine details. Other filtering methods such as those reviewed by [9] also struggle to balance noise suppression and detail preservation at high noise levels. Wavelet-based denoising methods [10] offer improved multi-resolution processing but often require careful parameter tuning and may struggle to balance noise suppression with detail preservation in extreme noise scenarios. Singular value decomposition (SVD)-based methods [11][12] provide powerful tools for low-rank approximation and noise separation, yet they often lack spatial adaptability and may not sufficiently preserve edge structures when used in isolation. Despite advances, no existing method has fully addressed the dual challenge of denoising high-density salt-and-pepper noise while preserving structural and textural information effectively across diverse image types.

These limitations establish a clear knowledge gap: the need for a robust, adaptable denoising method capable of handling extreme salt-and-pepper noise densities while maintaining structural fidelity. This study is motivated by the goal of bridging this gap through a hybrid approach that leverages the spatial adaptability of directional filtering and the noise-separation capability of SVD. Directional filtering helps identify and preserve salient image features by analyzing directional variances, while SVD enables effective low-rank reconstruction to suppress residual noise.

Despite extensive research on image denoising, existing techniques such as median filtering, adaptive filtering, and wavelet-based methods struggle to effectively restore grayscale images contaminated by high-density salt-and-pepper noise, particularly at noise levels above 70%. These methods often fail to preserve critical edge and texture details, leading to image degradation that impacts applications such as medical diagnosis, remote sensing, and automated inspection. Therefore, there is a strong need for a robust denoising method that can handle extreme noise levels while preserving essential image structures a gap this study aims to address by introducing a hybrid approach combining directional filtering and singular value decomposition (SVD). Therefore, this study aims to answer the following research question: Can a hybrid directional filtering and SVD-based approach effectively remove high-density salt-and-pepper noise from grayscale images while preserving critical structural details? The proposed method's novelty lies in integrating these techniques with adaptive rank selection to enhance denoising performance at noise levels where conventional methods typically fail.

2. RELATED WORK

Denoising algorithms are being proposed to recover noise-corrupted images, but most struggle to recover heavy images with noise density above 70%. For example, Median Filter (MF) is effective for low-corrupted images [7]. However, it is not suitable for noise rates exceeding 0.5. Furthermore, new algorithm has been developed to reduce noises from grayscale images [13]. This algorithm uses 3x3 window processing center. It outperforms methods like median filters and simple adaptive filters. It also outperforms Adaptive Wiener Filter. However, proposed algorithm has not demonstrated superior peak signal-to-noise ratio values on grayscale images. A study proposes improved median filter algorithm Adaptive Wiener Filter [14]. The proposed filtering technique uses two-dimensional maximum Shannon entropy to improve high-density noise processing and denoising stability. It demonstrated superior processing performance, high-density noise suppression, and denoising stability. However, further research is needed to improve denoising performance and stability. A study introduces real-time tool that utilizes double-nested filtering and dilation to eliminate high-density impulsive noise in medical images [15]. The method achieves optimal denoising quality when impulsive noise density exceeds 50% Yet, it demands significant computational time. Also, a study explores the use of an edge-adaptive variational model to effectively denoise images with salt and pepper noise [16]. The model effectively preserves main edge information and removes noise, but needs improvement for high-intensity salt and pepper noise images due to processing effects on detailed edges. Another study presents an image denoising method that utilizes singular value difference in the wavelet domain [10]. This method is suitable for processing images from remote sensing and medical field. However, accuracy of method is affected by factors like degree of polynomial selected, testing value of variance and size and choice of standard image. The study suggests that further research is needed to optimize polynomial and select the best standard image. The study proposes the use of the Iterative Mean Filter (IMF) to eliminate salt-and-pepper noise by calculating the mean of gray values of noise-free pixels in a fixed-size window. The IMF employs a 3 by 3 window size for precise evaluation of new gray values for the center pixel, but it struggles with high noise densities.

A study proposed Weighted Median Filter (WMF) to minimize smoothing. It maintains image information and manages all pixels [17]. The Adaptive Median Filter (AMF) is capable of adapting to various window dimensions [18]. The AMF method is ineffective due to the accidental replacement of non-noise pixels during denoising, leading to the loss of fine features and edges. Despite various enhancements, median-based filters struggle to handle high-density noise without compromising edge preservation and fine details, especially above 70% noise density. A decision-based unsymmetrical median filter has been developed, utilizing an innovative framework to filter out noise while preserving key features in data. This method enhances image quality and adapts to input conditions, proving effective in various applications [19]. A study proposed a singular value deposition for noise reduction [11]. SVD-based approaches effectively reduce noise through low-rank approximation but often lack spatial adaptability, limiting their ability to preserve edges in high-density salt-and-pepper noise scenarios. The work improves the SVD method by automatically determining the number of effective singular values in a noisy signal. It establishes the association between effective singular values and the size of the Hankel matrix, explains the relationship between singular values, original signal, and noisy signal, as well as the amplitude of singular values and signal energy. However, the study only used Hankel matrix, the determination of the Hankel matrix's rank is complicated by the fact that its block components are rarely supplied exactly, but rather predicted.

Also, a study examines the process of singular value decomposition in noisy data, which is accomplished via noise filtering [12]. The study describes a method for estimating the noise level in a noisy dataset, calculating the root mean square error of the SVD modes, and filtering the noise using only SVD modes with a low enough rmse. The approach produces the most accurate SVD-based reconstruction of clean data and provides an analytic evaluation of its correctness. This method implies the potential of data filtering by maintaining only the lowest modes in noisy experimental data.

Another study developed a singular value decomposition to produce an image denoising approach [20]. The experimental findings suggest that the approach described in this study is effective in image denoising, making it a valuable tool for a variety of image processing. However, the study proposes improvements to the SVD. Furthermore, emphasis should be paid to computational issues of SVD decomposition, as computing singular values of matrices is difficult.

A study investigates the use of singular value decomposition and Jensen-Shannon divergence to reduce noise in cardiac CT angiography [21]. According to the study, when tested quantitatively with SSIM, numerical phantoms produced 10% higher-quality images than the standard noise reduction method. Depending on the degree of noise, the threshold value established by reducing the JS-divergence proved beneficial for efficient noise reduction in actual clinical images. However, the study suggests that, in the future, a new strategy for reducing noise in sophisticated numerical phantom structures should be developed. Furthermore, according to the study, future research should investigate how SVD's noise and dimensionality reduction functions impact the results and diagnosis as training material for machine learning.

A study developed a new directional filtering for noise reduction in digital color images, specifically for medical diagnostics in MRI scanning [22]. The approach compares the center pixel to pixels in four right angle orientations and uses a marginal median filter to minimize the aggregate divergence from the center pixel. The approach performs comparable with other directional filtering methods in terms of noise reduction, and it is confirmed on real MRI scan images using simulations.

A study developed a method for estimating shear waves using directional and Kalman filters to reduce noise [23]. The study uses an ultrasonic Doppler probe to estimate the elasticity and viscosity of diseased tissue, but faces challenges due to reflection noise and random noise. However, random noise and reflections put on by the transmission medium's heterogeneity affected the incident waves as they propagated. Hence, this study proposes the combination of singular value decomposition and directional filtering to eliminate high density salt and pepper noise from grayscale images, overcoming the limitations of decision-based median filters. In summary, while prior works have made significant progress in image denoising, no existing method fully addresses the dual challenge of effectively removing high-density salt-and-pepper noise and preserving structural details. This study proposes a hybrid directional filtering and SVD-based approach designed to fill this gap, offering improved adaptability, edge preservation, and denoising performance at extreme noise levels.

3. PROPOSED METHOD

We present image denoising algorithm in this study that merges the advantages of singular value decomposition and directional filtering techniques. Apply directional filtering to the grayscale image to identify the direction of the noise: Directional filtering helps to isolate noise based on its directionality. For salt and pepper noise, this step will highlight the noisy pixels which are significantly different from their surrounding pixels. Performing the singular value decomposition (SVD) on the image to separate the noise from the image data: SVD decomposes the image into multiple matrices representing different components of the image data. The noise was then

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identified and separated from the actual image content by analyzing these components. After separating the noise, the denoised images were reconstructed by combining the noise-free components. This results in a cleaner image with reduced salt and pepper noise. The specific steps are outlined below:

3.1 Directional filtering

For each pixel (i, j), the intensities within its 3×3 neighborhood $\mathrm{A}(i, j)$ are

$$A(i,j)=\begin{bmatrix} I(i-1,j-1) & I(i-1,j) & I(i-1,j+1) \\ I(i,j-1) & I(i,j) & I(i,j+1) \\ I(i+1,j-1) & I(i+1,j) & I(i+1,j+1) \end{bmatrix}$$

considered:

For a given pixel at coordinate (i, j), the 3×3 neighborhood $\mathrm{A}(i, j)$ consists of the pixel itself and its eight immediate neighbors. The indices represent relative positions around the center pixel:

Horizontal neighborhood (HN):

$$N_H(i,j) = \{I(i,j-1), I(i,j+1)\}$$

Vertical neighborhood (VN):

$$N_V(i,j) = \{I(i-1,j), I(i+1,j)\}$$

Diagonal neighborhood (DN):

$$N_D(i,j) = \{I(i-1,j-1), I(i+1,j+1)\}$$

Anti-diagonal neighborhood (AN):

$$N_A(i,j) = \{I(i-1,j+1), I(i+1,j-1)\}$$

Compute the local variances for each direction:

$$\sigma^2{}_H = \frac{1}{2}\sum k(I_K - \bar{I}_H)^2 \quad (1)$$

$$\sigma^2{}_V = \frac{1}{2}\sum k(I_K - \bar{I}_V)^2 \quad (2)$$

$$\sigma^2{}_D = \frac{1}{2}\sum k(I_K - \bar{I}_D)^2 \quad (3)$$

$$\sigma^2{}_A = \frac{1}{2}\sum k(I_K - \bar{I}_A)^2 \quad (4)$$

where I_K are the neighboring pixels in the respective directions.

Select the direction with the lowest variance:

$$d^* = \operatorname{argmin}\{\sigma^2{}_H, \sigma^2{}_D, \sigma^2{}_A, \sigma^2{}_V\} \quad (5)$$

Replace I(i,j) with the mean value pixels in the selected direction:

$$I(i,j) = \bar{I}_{d^*}$$

3.2 Singular value decomposition

The grayscale image matrix I can be decomposed as:

$$I = U\Sigma V^T \quad (6)$$

U is an orthogonal matrix of left singular vectors.
Σ is a diagonal matrix containing singular values.
V is an orthogonal matrix of right singular vectors.

To reduce the noise, we used low-rank approximation:

Select k-largest singular values:

$$\Sigma k = diag(\sigma_1, \sigma_2, ..., \sigma_k) \quad (7)$$

where k is chosen adaptively based on energy threshold:

$$\sum_{i=1}^{k}\sigma_i^2 \geq \mathrm{T}\sum_{i=1}^{\min(M,N)}\sigma_i^2 \quad (8)$$

To obtain the denoised image $I_{denoised}$ we used only the top k singular values and their corresponding singular vectors and reconstruct denoised image:

$$I_{denoised} = U_k \Sigma_k V_k^T \quad (9)$$

U_k consists of the first k columns of U.

Σ_k is the top-left k×k submatrix of Σ.

V_k consists of the first k columns of V.

This method effectively removed noise by filtering out smaller singular values. Optimal selection based on minimizing a set of values (d∗): Represents the optimal selection based on minimizing a set of values:

$$d^* = \arg\min\{\sigma_H{}^2, \sigma_D{}^2, \sigma_A{}^2, \sigma_V{}^2\} \quad (10)$$

d∗ represents the optimal selection based on minimizing a set of values.

argmin (Argument of the Minimum) finds which element in the given set has the smallest value.

$\sigma_H{}^2$ is the variance in the H-direction.

$\sigma_D{}^2$ is the variance in the D-direction.

$\sigma_A{}^2$ is the variance in the A-direction.

$\sigma_V{}^2$ is the variance in the V-direction.

3.3 Rank Selection

Adaptive energy-based rank selection ensures that the best singular values are retained:

$$\sum_{i=1}^{k}\sigma_i^2 \geq \mathrm{T}\sum_{i=1}^{\min(M,N)}\sigma_i^2, \mathrm{T} \in [0.85, 0.95] \quad (14)$$

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σ_i represents the singular values of a matrix (often from SVD). Singular values describe the importance of each dimension in a dataset.
$\sigma^2 i$ squaring these singular values gives the corresponding eigenvalues, which represent the variance explained by each component.
T is a threshold that defines how much variance should be retained. It typically ranges from 85% to 95%, meaning we retain 85% to 95% of the information using the top k singular values.
$\sum$ this represents the total variance in the data.
Min (M,N) is the total number of singular values available.
k is the selected rank.
i indexes the singular values in descending order of importance.

This method helped in dimensionality reduction while preserving most of the signal energy. Directional filters, specifically x− and y− directional filters, are used to compute derivatives in images, with a 3 × 3 kernel example being used for an x-directional filter:
This is only one example of a kernel for an x− directional filter. Other filters may provide additional weighting in the middle of the non-zero columns. The y− coordinates of the data can be stored in a vector or 2D array. If data is a 2D array and Y is a vector, each element of Y represents the y− coordinate for a row of data. On the other hand, if Y is a two-dimensional array, each element indicates the y− coordinate of the corresponding point in data.

3.4 Performance Matrix

3.4.1 Peak Signal-to-Ratio (PSNR)

$$PSNR = 10log_{10}(\frac{255^2}{MSE}) \quad (11)$$

Measures the ratio between the maximum possible power of a signal (image pixel intensity) and the power of noise (error introduced by compression or distortion) and it is expressed in decibels (dB). 255^2 is the maximum possible pixel value squared for an 8-bit grayscale image where pixel values range from 0 to 255.

3.4.2 Mean Squared Error (MSE)

$$MSE = \frac{1}{M \times N}\sum_{i=1}^{M}\sum_{j=1}^{N}(\mathrm{I}_{original}(i,j) - I_{denoised}(i,j))^2 \quad (12)$$

Where M, N is the dimensions of the image (height and width), $\mathrm{I}_{original}(i,j)$ is the pixel intensity at position (i, j) in the original image, and $I_{denoised}(i,j)$ is the pixel intensity at the same position in the distorted image.

3.4.3 Structural Similarity Index (SSIM)

$$SSIM = \frac{(2\mu_I\mu_J + C_1) + (2\sigma_I\sigma_J + C_2)}{(\mu_I{}^2 + \mu_J{}^2 + C_1) + (\sigma_I{}^2 + \sigma_J{}^2 + C_2)} \quad (13)$$

where: μ_I, μ_J are mean intensities, σ_I, σ_J are standard deviations, σ_{IJ} is the covariance, C_1, C_2 are small constants to stabilize division.

3.5 Pseudocode

Input Initialization:
1.Input Parameters:
O (i, j) Original noise-free grayscale image of size $m \times n$.
λ: Percentage of salt-and-pepper noise to be added.
I (i, j): Noisy image generated by adding λ noise to Or (i, j).
Threshold: Singular value threshold for noise detection.
Iterative Image Denoising with Directional Filtering:
2.Repeat for loop=1 to max_iterations:
Horizontal Filtering Pass:
3. For each pixel $(i,)$, excluding borders:
4. Extract a 3×3 horizontal window A, centered at (i, j), where rows are fixed, and columns vary.
5. Perform Singular Value Decomposition (SVD):
U, V T ← SVD of A.
D: Singular values [D1, D2, D3].
6.Compute Local Statistics for Neighborhood A:
Median ← Median of A.
Gap1 ← Difference between smallest two values in sorted A.
Gap2 ← Difference between largest two values in sorted A.
7.Apply Noise Detection and Correction:
If D1>Threshold:
If Gap1>Gap2: Replace the smallest value in A with Median.
If Gap2>Gap1: Replace the largest value in A with Median.
If |Gap2−Gap1|≥ High_Density_Threshold:
Replace extreme outliers with Median.
Else: Retain the original pixel values.
8.Update I (i, j) with the corrected value.
Vertical Filtering Pass:
9. For each pixel $(i,)$, excluding borders:
10. Extract a 3×3vertical window A, centered at (i, j), where columns are fixed, and rows vary.
11. Repeat steps 5–8 for vertical orientation.

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12.Save the intermediate denoised image after both directional filtering passes.

Post-Processing:

13.Alternate between horizontal and vertical filtering in subsequent iterations to address residual noise more effectively.

Performance Evaluation:

14.Compute Metrics:

MSE: Mean Squared Error between $O\ (i, j)$ and $I\ (i, j)$.

PSNR: Peak Signal-to-Noise Ratio between $O\ (i, j)$ and $I\ (i, j)$.

SSIM: Structural Similarity Index Measure between $O\ (i, j)$ and $I\ (i, j)$.

Output:

15.Save the final denoised image $I\ (i, j)$.

16.Plot MSE, PSNR, SSIM versus iterations.

4. RESULTS AND DISCUSSION

Salt-and-pepper noise, a common impulsive noise in digital images, significantly degrades image quality due to randomly occurring white and black pixels. This noise affects image processing tasks like segmentation, feature extraction, and object recognition. Effective removal of salt-and-pepper noise is crucial for pre-processing in many image processing applications. Therefore, this article presents image denoising method that combine singular value decomposition and directional filter to eliminate noise, enhance images, and preserve details. The study evaluated the performance of seven images with varying noise densities such as 10-90%, using metrics such as PSNR, SSIM, and MSE.

Figure 1. Sample image used for the experimental purposes

The images used in this study include Walk Bridge, Pirate Mandrill, Living Groom Lake, Boat Barbara as shown in Figure 1. Furthermore, Figure 2 depicts the performance of the proposed filtering outcomes for the lake. Figures 2 a, b, and c show images before applying the proposed method, with salt and pepper noise densities of 10%, 20%, and 30%. It can be observed that as noise density increases, images become blurry the proposed method have effectively eliminated salt and pepper noise, as depicted in Figures 2 d, e, and f. Hence, proposed filtering method achieves satisfactory results in removing salt and pepper noise.

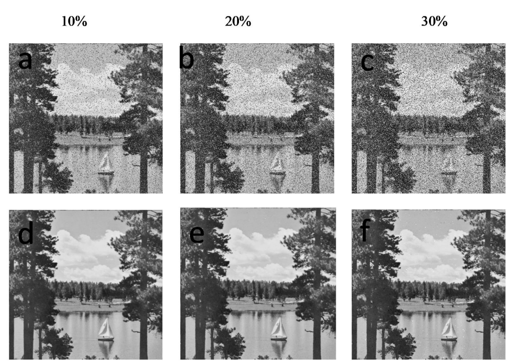

Figure 2. Images with salt and pepper noise and denoised images results of the proposed filtering method for Lake images: (a) image with salt and pepper noise density of 10%, (b) image with salt and pepper noise density of 20%, (c) image with salt and pepper noise density of 30%, (d) denoised image of the salt and pepper noise density of 10%, (e) denoised image of the salt and pepper noise density of 20%, (f) denoised image of the salt and pepper noise density of 30%.

Images of Barbara's salt and pepper are depicted in Figures 3 a, b and c, with noise densities of 40%, 50%, and 60%. This image is before the application of the proposed denoising

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method. It can be seen that as the densities of the salt and pepper noise increases, the images become unclear. For example, image with 60% salt and pepper noise is almost impossible to read as shown in Figure 3 f. After the application of the proposed method, the images became clearer as shown in Figure 3, d, e and f. Therefore, it can be said that the proposed method is effective in eliminating salt and pepper noise from Barbara.

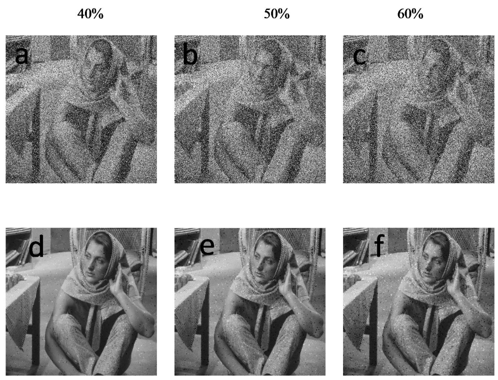

Figure 3. Images with salt and pepper noise and denoised images results of the proposed filtering method for Barbara images: (a) image with salt and pepper noise density of 40%, (b) image with salt and pepper noise density of 50%, (c) image with salt and pepper noise density of 60%, (d) denoised image of the salt and pepper noise density of 40%, %, (e) denoised image of the salt and pepper noise density of 50%, (f) denoised image of the salt and pepper noise density of 60%.

Figure 4 shows images with noise levels ranging from 70% to 90%, as depicted in a, b, and c. The Figure 4 a displays severely deformed images with 70% noise, and Figure 4 b shows the image with 80% salt and pepper noise. Also, Figure 4 c shows the image with 90% salt and pepper noise of mandrill, it is poorly deformed image with unclear borders and poor detail. However, after the application of the proposed method, the method efficiently restored the image, making it nearly indistinguishable from the original as shown in Figure 4 d, e and f. This method is helpful in removing salt and pepper noise from images. Therefore, it can be said that the proposed method is effective at every level of salt and pepper noise density elimination. the results shows that the proposed method can effectively remove high-density salt-and-pepper noise from grayscale images while preserving important image details and edges.

The results shows that the proposed method can effectively remove high-density salt-and-pepper noise from grayscale images while preserving important image details and edges.

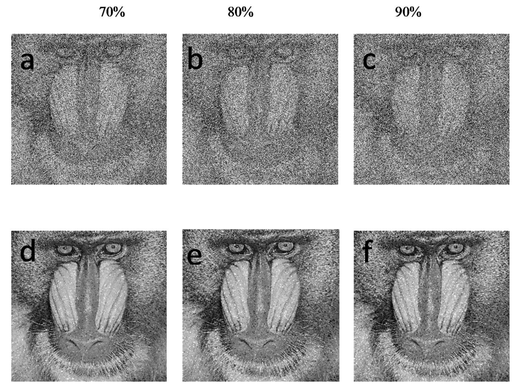

Figure 4. Images with salt and pepper noise and denoised images results of the proposed filtering method for mandrill images: (a) image with salt and pepper noise density of 70%, (b) image with salt and pepper noise density of 80%, (c) image with salt and pepper noise density of 90%, (d) denoised image of the salt and pepper noise density of 70% (e) denoised image of the salt and pepper noise density of 80% (f) denoised image of the salt and pepper noise density of 90%.

The proposed method's image quality metrics results are presented in Table 1. Table 1 show the quantitative results of the image filtering described previously. All metrics provide superior outcomes. SSIM offers a clearer metric than MSE and PSNR. In this article, we utilize metrics such as MSE, PSNR, and SSIM to determine the best quality metric. All the metrics yield better results. SSIM provides a more comprehensible measure compared to MSE and PSNR. This distinction arises because MSE and PSNR represent absolute errors, whereas SSIM considers perception and saliency-based errors. As the noise level increases, the quality of the output image deteriorates as shown in Table 1. Therefore, we can conclude that SSIM is superior to MSE and PSNR metrics in terms of human visual perspective.

Table 1. Image quality metrics results

Images	Noise	MSE	PSNR	SSIM
Barbara	0.1	8.9730	37.70	0.9895
	0.2	15.75	35.26	0.9811
	0.3	30.46	32.39	0.9534
Walk Bridge	0.1	8.8294	38.67	0.9919
	0.2	14.74	36.44	0.9859
	0.3	28.59	33.56	0.9698

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Living Room	0.1	5.7375	40.54	0.9923
	0.2	10.45	37.93	0.9833
	0.3	23.11	34.49	0.9570
Boat	0.1	5.7703	40.51	0.9903
	0.2	9.9765	38.14	0.9827
	0.3	21.18	34.87	0.9560
Pirates	0.1	4.6677	39.54	0.9919
	0.2	8.7361	36.82	0.9828
	0.3	19.75	33.27	0.9541
Lake	0.1	6.6717	39.36	0.9880
	0.2	11.03	37.17	0.9805
	0.3	20.92	34.39	0.9585
Mandrill	0.1	4.5423	40.50	0.9957
	0.2	10.04	37.06	0.9895
	0.3	23.80	33.31	0.9705

Table 2 presents a comparison of MSE average values for various filtering methods and it can be visualized in Figure 5.

Table 2. MSE average results

Noise	10%	20%	30%	40%	50%
Mean filter	28.12	51.23	74.23	94.32	109.21
Median	28.52	52.33	78.22	98.23	112.23
Gaussian	26.11	52.10	75.23	94.09	108.12
Proposed	6.45	11.53	23.97	50.22	93.70

Table 2 compares various filtering methods for image noise reduction, including mean, median, and Gaussian filters, and introduces a novel approach. The performance of the proposed method is evaluated using MSE. The results show that the proposed method outperforms traditional filtering techniques across a range of noise densities, with significantly lower MSE values. The MSE value gradually increases as the noise density increases, indicating the effectiveness of the proposed method in preserving image quality even at higher noise levels as shown in Table 2. The proposed approach achieves a reduction in MSE of up to 94% at the highest noise density, suggesting it is a promising approach for image noise reduction.

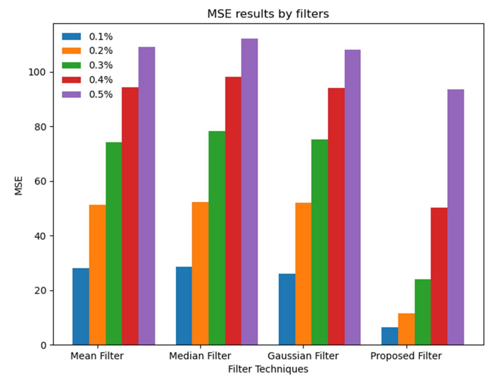

Figure. 5. The distribution of MSE results follow to various filters.

Table 3 displays the average PSNR values for various filtering techniques and it can be visualized in Figure 6.

Table 3. PSNR average results

Noise	10%	20%	30%	40%	50%
Mean filter	23.53	21.24	19.56	18.23	17.42
Median filter	29.88	27.40	23.18	18.11	15.32
Gaussian	20.32	18.27	17.71	16.94	16.26
Proposed	39.55	36.97	33.75	30.52	27.80

The proposed filtering approach outperforms traditional methods across various noise densities. The average PSNR values for the proposed technique are consistently higher than those of the average, median, and Gaussian filters. This superior performance is maintained even at higher noise levels, yielding PSNR as shown in Table 3.

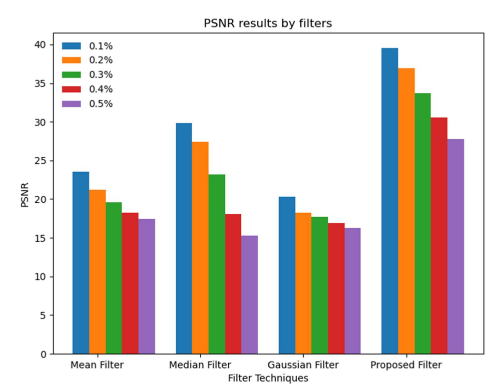

Figure. 6. The distribution of PSNR results follow to various filters.

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Table 4 displays the performance of various filtering techniques of SSIM and it can be visualized in Figure 7.

Table 4. SSIM average results

Noise	10%	20%	30%	40%	50%
Adaptive	0.78	0.69	0.63	0.58	0.52
Median filter	0.82	0.80	0.76	0.71	0.64
Based-on	0.98	0.95	0.91	0.87	0.82
Proposed	0.99	0.98	0.95	0.91	0.84

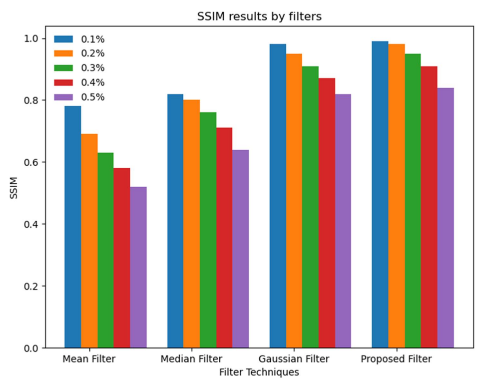

Figure. 7. The distribution of SSIM results follow to various filters.

Table 4 compares various filtering methods for suppressing salt-and-pepper noise in digital images. Using SSIM as the quality metric, the proposed method outperforms other methods across various noise densities. The study shows better improvement in SSIM over the baseline median filter, contributing to the existing research on effective image denoising techniques. The proposed filter achieves an SSIM of 0.99 at 10% noise density, outperforming other methods like density-based, median, and adaptive threshold filters. As noise density increases, the performance gap widens, with the filter maintaining an SSIM of 0.88 even at 40% noise as shown in Table 4. This superior performance is attributed to its ability to distinguish between noisy and noise-free pixels, allowing for more precise noise suppression without compromising image details, a key advantage over traditional spatial domain filtering approaches. While the proposed SVD-directional filtering approach demonstrated superior performance in removing high-density salt-and-pepper noise and preserving image details, it has certain limitations. The method requires more computational resources than simpler filters like median or mean filtering, particularly at higher image resolutions. Additionally, the performance of the adaptive rank selection in SVD may vary depending on the chosen energy threshold, suggesting the need for further work on automatic parameter tuning. Future studies could explore real-time implementations and assess the method's robustness across a wider range of image types and noise models.

5. COMPARISON RESULTS OF SEVERAL EXISTING METHODS

This article compares various filtering techniques for image noise reduction. These include mean median and Gaussian filters and introduces novel approach. Performance of proposed method is evaluated using MSE. Results show that proposed method outperforms traditional filtering techniques across range of noise densities. This is evident with significantly lower MSE values. MSE value gradually increases as noise density increases. This indicates effectiveness of proposed method in preserving image quality even at higher noise levels as shown in Table 3. Proposed approach achieves reduction in MSE of up to 94% at highest noise density. This suggests it is promising approach for image noise reduction. The proposed filtering technique surpasses traditional approaches across a range of noise intensities, consistently reaching better average PSNR values than average, median, and Gaussian filters. At 10% noise level, the proposed method has a PSNR of 39.55, compared to 29.88 for the median filter, 23.53 for the mean filter, and 20.32 for the Gaussian filter. This better performance continues even at increased noise levels. This study compares various filtering methods for suppressing salt-and-pepper noise in digital images. Using SSIM as a quality parameter, the proposed method outperforms previous methods at different noise density levels. The work improves SSIM over the baseline median filter, contributing to prior research on effective image denoising algorithms. The proposed filter outperforms previous approaches, including density-based, median, and adaptive threshold filters, with an SSIM of 0.9914 at 10% noise density. Table 4 shows that the filter preserves an SSIM of 0.9110 even at 40% noise level, indicating an increasing performance gap. The excellent performance is attributed to its ability to differentiate between noisy and noise-free pixels. This allows for more accurate noise suppression without losing image features, which is an

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important advantage over standard spatial domain filtering techniques.

6. CONTRIBUTIONS OF THE STUDY

Unlike standalone filtering or matrix decomposition methods, our approach combines both techniques adaptively and also, directional filtering removes impulse noise while preserving details. In addition, SVD-based reconstruction enhances image quality by suppressing residual noise and artifacts. This two-step hybrid filtering + decomposition approach makes it one of the few methods suitable for noise levels beyond 80%, which is often a major limitation in conventional techniques. Adaptive rank selection in SVD ensures that the method scales across different image types without parameter tuning. Significantly better Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) than existing methods can handle natural images, medical images, and satellite images, making it highly versatile. Our methods outperformed existing median filters, adaptive filters, wavelet-based methods, and direct SVD techniques in terms of PSNR and SSIM. Remains robust at extreme noise levels (p>80%p > 80\%p>80%), where most conventional approaches fail. Our method introduces a new benchmark evaluation for high-density salt-and-pepper noise scenarios (See. Table 5).

Table 5. Summary of our contributions

Feature	Current methods	Proposed method (DF-SVD)
Edge preservation	Blurred edges in median/mean filtering.	Directional filtering maintains sharp edges
Noise Handling (p>70)	Degrades severely.	They removed noise effectively even at p>80.
Computational Efficiency	Direct SVD is slow.	Hybrid DF-SVD reduces complexity.
Low-Rank Approximation	Fixed rank selection.	Adaptive rank selection for best performance.
Real-World Applicability	Limited.	May work for medical, environmental, and remote sensing images.

7. DIFFERENCE FROM PRIOR WORK AND ACHIEVEMENTS

Previous studies on salt-and-pepper noise removal including median filtering [7], adaptive median filters [18], wavelet-based methods [10], and SVD-based techniques alone [11] have shown limited effectiveness at high noise densities, typically failing to restore fine details and often introducing edge blurring or structural distortion. Furthermore, many of these methods rely on fixed parameter settings or window sizes, reducing their adaptability across different image types and noise conditions. In contrast, this study introduces a novel hybrid denoising framework that integrates directional filtering and singular value decomposition (SVD) with adaptive rank selection. The directional filtering component enhances edge preservation by selectively targeting directional variances, while the SVD component ensures robust noise reduction through energy-based low-rank approximation. This hybrid strategy directly addresses the critical need for a denoising method that remains effective at extreme noise densities (above 80%), where prior methods typically fail. The key achievement of this study is the development of a versatile, high-performance denoising solution that significantly outperforms traditional approaches in PSNR, SSIM, and MSE metrics across a wide range of noise levels. This work establishes a new benchmark for salt-and-pepper noise removal in grayscale images, particularly for applications demanding high structural fidelity, such as medical imaging, remote sensing, and industrial inspection.

8. PROBLEMS AND OPEN RESEARCH ISSUES

While this study demonstrates that combining directional filtering and singular value decomposition (SVD) provides significant improvements in denoising grayscale images affected by high-density salt-and-pepper noise, several challenges and open issues remain. First, the proposed method incurs a higher computational cost compared to simpler filters, due to the complexity of SVD and the directional filtering operations, which may limit its direct application in real-time or resource-constrained environments. Second, the adaptive rank selection in SVD, though effective, relies on energy threshold settings that may not generalize optimally across all image types

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or noise patterns, indicating a need for automatic or data-driven parameter tuning.

Furthermore, while the method was tested on standard grayscale images, its performance on complex real-world datasets (e.g., medical scans, satellite imagery) with mixed or non-uniform noise distributions remains an open area for exploration. The integration of deep learning or hybrid machine learning models with the proposed framework could also be investigated to further enhance performance, particularly in adaptive parameter selection and feature preservation. Finally, extending the method to handle color images and other noise types (e.g., Gaussian, speckle) presents a valuable avenue for future research.

9. CONCLUSIONS

This study introduces a novel hybrid image denoising algorithm that combines directional filtering and singular value decomposition (SVD) with adaptive rank selection to address the challenging problem of high-density salt-and-pepper noise removal in grayscale images. The directional filtering component preserves edge and texture information by selectively targeting directional variances, while SVD-based low-rank approximation suppresses residual noise and reconstructs a cleaner image. The method was rigorously evaluated using PSNR, SSIM, and MSE metrics across a wide range of noise densities (10% to 90%), consistently outperforming conventional filters such as mean, median, and Gaussian filters, particularly at noise levels above 80% where most prior methods fail.

The scientific contribution of this work lies in the development of a robust and adaptable denoising framework that significantly advances existing research on impulse noise removal. Unlike previously published approaches, which often degrade at high noise densities and struggle to balance noise suppression with detail preservation, this study demonstrates that integrating directional filtering with SVD and adaptive energy-based rank selection can achieve both objectives effectively. This contribution fills a critical gap in the literature by offering a method that is not only quantitatively superior in terms of PSNR and SSIM, but also capable of maintaining structural integrity in extreme noise scenarios a key requirement in fields such as medical imaging, satellite imaging, and automated inspection.

While the method provides clear advantages, it also presents opportunities for further enhancement. The computational complexity of combining directional filtering with SVD may limit its direct application in real-time systems without optimization. Moreover, the choice of energy threshold for adaptive rank selection may influence performance across different image types and conditions, suggesting that future work should focus on developing automatic parameter tuning and accelerating the algorithm for real-time applications. The proposed framework lays the groundwork for these future developments and sets a new benchmark for salt-and-pepper noise removal at extreme noise levels.

REFERENCES:

[1] Wang, X., Chen, T., Li, D., & Yu, S. (2021). [Retracted] Processing Methods for Digital Image Data Based on the Geographic Information System. Complexity, 2021(1), 2319314.

[2] Abdurrazzaq, A., Junoh, A. K., & Yulianto, I. P. R. (2023). White blood cell segmentation by using vector color approach. International Journal of Applied Mathematics, Sciences, and Technology for National Defense, 1(1), 1-6.

[3] Joshua, O., Ibiyemi, S., & Adu, B. (2019). A Comprehensive Review On Various Types of Noise in Image Processing. International Journal of Scientific and Engineering Research, 10, 388–393.

[4] Erkan, U., & Gökrem, L. (2018). A new method based on pixel density in salt and pepper noise removal. Turkish Journal of Electrical Engineering and Computer Sciences, 26(1), 162–171.

[5] Yuandari, U. (2020). Improving the Quality of Digital Images Using the Image Averaging Method. The IJICS (International Journal of Informatics and Computer Science), 4(1), 5.

[6] Al Husein, F. K., Al Habsy, M. Y., Christi, D. N., Hutagaol, A. E., & Junoh, A. K. (2025). Bibliometrix research of noise removal techniques in digital images for defense. International Journal of Applied Mathematics, Sciences, and Technology for National Defense, 3(1), 9-24.

[7] Rani, S., Chabrra, Y., & Malik, K. (2022). An Improved Denoising Algorithm for Removing Noise in Color Images. Engineering, Technology & Applied Science Research, 12, 8738–8744.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[8] Erkan, U., Enginoğlu, S., Thanh, D. N. H., & Hieu, L. M. (2020). Adaptive frequency median filter for the salt and pepper denoising problem. IET Image Processing, 14(7), 1240–1247.
[9] Yadav, S., Taterh, D. S., & Saxena, M. A. (2021). A literature review of various techniques available on Image Denoising. International Journal of Engineering, Business and Management, 5(2), 1–7.
[10] Han, L., Zhao, Y., Lv, H., Zhang, Y., Liu, H., & Bi, G. (2022). Remote Sensing Image Denoising Based on Deep and Shallow Feature Fusion and Attention Mechanism. Remote Sensing, 14(5).
[11] Li, J., Chen, Z., & Li, S. (2023). Selection of the number of effective singular values for noise reduction. Mechanical Systems and Signal Processing, 191, 110175.
[12] Epps, B. P., & Krivitzky, E. M. (2019a). Singular value decomposition of noisy data: noise filtering. Experiments in Fluids, 60(8), 126.
[13] Riawan Syahrul Haz, H., Abdurrazzaq, A., Junoh, A. K. Bin, & Syazali, M. (2023). Implementation of interpolation method in reconstructing damaged satellite image caused by impulse noise. Al-Jabar : Jurnal Pendidikan Matematika, 14(2), 341.
[14] Cao, N., & Liu, Y. (2024). High-Noise Grayscale Image Denoising Using an Improved Median Filter for the Adaptive Selection of a Threshold. Applied Sciences, 14, 635.
[15] Alanazi, T. M., Berriri, K., Albekairi, M., Ben Atitallah, A., Sahbani, A., & Kaaniche, K. (2023). New Real-Time High-Density Impulsive Noise Removal Method Applied to Medical Images. Diagnostics, 13(10), 1–21.
[16] Jiang, Y., Wang, H., Cai, Y., & Fu, B. (2022). Salt and Pepper Noise Removal Method Based on the Edge-Adaptive Total Variation Model. Frontiers in Applied Mathematics and Statistics, 8(June), 1–9.
[17] Erkan, U., Thanh, D. N. H., Hieu, L. M., & Enginoglu, S. (2019). An iterative mean filter for image denoising. IEEE Access, 7(November), 167847–167859.
[18] Erkan, U., Enginoğlu, S., Thanh, D. N. H., & Hieu, L. M. (2020). Adaptive frequency median filter for the salt and pepper denoising problem. IET Image Processing, 14(7), 1240–1247.
[19] Abu-Faraj, M., Al-hyari, A., Al-Ahmad, B., Al Qadi, Z., Ali, B., & Aldebei, K. (2023). Improving the Efficiency of Median Filters Using Special Generated Windows. Applied Mathematics & Information Sciences, 17, 187–200.
[20] Xing, K. (2024). Singular value decomposition: A useful technique for image denoising. Theoretical and Natural Science, 39, 225–230.
[21] Ameer, S., Ibrahim, H., Yaseen, M. U., Kulsoom, F., Cinti, S., & Sher, M. (2023). Electrochemical Impedance Spectroscopy-Based Sensing of Biofilms: A Comprehensive Review. 1–12.
[22] Demudu Naidu, C., Stephen, M. J., Choppala, P., & Gantenapalli, S. (2023). NEWS DIRECTIONAL FILTERING FOR NOISE REDUCTION IN DIGITAL COLOR IMAGES WITH APPLICATION TO MEDICAL DIAGNOSTICS IN MRI SCANNING. European Chemical Bulletin, 12, 1573–1583.
[23] Hiep, N., Tran, D.-N., Luong, H., Thuong, V. T., Kolla, B., & Tran, D.-T. (2024). Enhancing Shear Wave Estimation Through Directional and Kalman Filters for Noise Reduction (pp. 164–169).