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Adaptive Weighted Mean-Median Filtering for Robust Salt-and-Pepper Noise Removal Technique

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Abstract. The primary challenge with image processing applications in automated surveillance, medical, and remote sensing is image denoising. Salt-and-pepper noise (SAPN) drastically reduces image quality by randomly changing pixel values with high intensities. At higher noise densities, the fundamental challenge for conventional filtering algorithms is to balance noise suppression and detail retention. In digital image processing applications accuracy is very important. However, during capturing and transmission, the images are exposed to various noise frequently. In this research article, an Adaptive Weighted Mean-Median Filter (AWMMF) is proposed for robust Salt-and-Pepper Noise Removal Technique. In the proposed work the filtering window size is dynamically adjusted according to the local noise density. AWMMF integrates a weighted combination of mean and median values to enhance restoration quality while preserving image details. The efficacy of the proposed algorithm is evaluated on standard benchmark Lena image and compared with existing denoising techniques like Adaptive Fuzzy Median Filter, Fast and Efficient Median Filter, Nonlinear Hybrid Filter, Improved Adaptive Type-2 Fuzzy Filter, Regeneration Filter, Deep Convolutional Neural Network and Adaptive Switching Modified Decision-Based Unsymmetric Trimmed Median Filter. For the performance analysis, the parameters considered are the Peak Signal-to-Noise Ratio, Mean Squared Error, Structural Similarity Index and Image Enhancement Factor. AWMMF provides a robust and computationally efficient solution for SAPN removal, making it suitable for real-world image processing applications.

Keywords: Adaptive Filtering, Image Denoising, Image Enhancement Factor, Mean Squared Error, Salt-And-Pepper Noise

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Адаптивный метод взвешенной фильтрации для удаления шума типа «соль и перец»

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Реферат. Основной проблемой обработки изображений в системах автоматизированного наблюдения, медицины и дистанционного зондирования является устранение шума на изображениях. Шум типа «соль и перец» (Salt-and-pepper noise – SAPN) существенно снижает качество изображения по причине случайного и интенсивного изменения значений пикселей. При более высоких плотностях шума основной проблемой традиционных алгоритмов фильтрации становится поиск баланса между подавлением шума и сохранением деталей сигнала. При цифровой обработке изображений точность проводимых операций очень важна. Однако во время съемки и передачи изображений они часто подвергаются воздействию различных шумов. В данной исследовательской статье предлагается использовать адаптивный взвешенный среднемедианный фильтр (Adaptive Weighted Mean-Median Filter – AWMMF), который обеспечивает надежное применение метода, предназначенного для удаления шума типа «соль и перец». Размер окна фильтрации динамически регулируется в зависимости от локальной плотности шума. Адаптивный взвешенный среднемедианный

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фильтр объединяет взвешенную комбинацию средних и медианных значений для обеспечения улучшения качества восстановления, сохраняя при этом детали изображения. Эффективность предлагаемого алгоритма оценивается на стандартном эталонном изображении Lena и сравнивается с такими существующими методами шумоподавления, как адаптивный нечеткий медианный фильтр, быстрый и эффективный медианный фильтр, нелинейный гибридный фильтр, улучшенный адаптивный нечеткий фильтр типа 2, фильтр регенерации, глубокая сверточная сеть и адаптивный коммутационный модифицированный несимметричный усеченный медианный фильтр на основе принятия решений. При анализе качества работы предлагаемого метода учитываются следующие параметры: пиковое отношение сигнала, среднеквадратичная ошибка, индекс структурного сходства и коэффициент улучшения изображения. Адаптивный взвешенный среднемедианный фильтр обеспечивает надежное и эффективное решение для удаления шума типа «соль и перец», что позволяет использовать его для реальных приложений обработки изображений.

Ключевые слова: адаптивная фильтрация, шумоподавление изображения, коэффициент улучшения изображения, среднеквадратичная ошибка, шум типа «соль и перец»

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Introduction

In Image denoising is the major issue in the applications of image processing in the fields of remote sensing, medical, and automated surveillance. The salt-and-pepper noise (SAPN) is one of the noises that significantly degrades image quality by randomly replacing pixel values with extreme intensities. In conventional filtering techniques, the main problem is to balance noise suppression and detail preservation, at higher noise densities.

Moreover, in the digital image processing domain, the accuracy of visual data is very important. However, during capturing and transmission, pictures are frequently vulnerable to several kinds of noise. Salt-and-pepper noise (SAPN) is a common type of impulsive noise in the form of random black-and-white pixels, which considerably diminishes image quality and affects subsequent image evaluation processes. Effective removal of SAPN is, therefore, a critical endeavor in enhancing image fidelity.

Conventional denoising techniques, such as the Standard Median Filter (SMF), have been widely employed due to their simplicity and effectiveness in low noise densities. To effectively eliminate the noise candidate the SMF replaces each pixel's value with the median value of the intensities in its neighborhood. However, its performance deteriorates at higher noise levels, leading to blurring and loss of vital image details [1]. In the modified version of SMF the size of the filtering window is dynamically adjusted based on local noise density, aiming to preserve edges while removing noise. Despite its adaptive nature, the AMF can result in excessive smoothing, especially in images with high-density noise, thereby compromising edge and detail preservation [2]. Recent advancements have seen the emergence of sophisticated methods that blend traditional filtering techniques with modern computational approaches. For instance, the Edge-Adaptive Total Variation (EATV) model segments images into edge and non-edge regions, applying total variation denoising selectively to maintain edge integrity while suppressing noise. This method has demonstrated improved performance in balancing noise reduction and detail preservation [3]. Another notable approach is the Detail-Aware Filter (DAF), which combines median filtering with an adaptive non-local means filter. This hybrid technique effectively reduces noise while retaining intricate image details, outperformming traditional methods in various scenarios [4]. In the realm of high-density noise conditions, the Nonlinear Hybrid Filter (NHF) has been proposed. This filter integrates mathematical morphology operations with a trimmed median filter, enhancing robustness against noise while preserving essential image features [1]. The Regeneration Filter (RF) offers a different strategy by selectively processing noisy pixels based on local context, thereby preserving structural details even in heavily corrupted images [2]. Fuzzy logic-based methods have also gained traction, with the Improved Adaptive Type-2 Fuzzy Filter (IAT2FF) employing type-2 fuzzy logic to distinguish between noisy and noise-free pixels. This approach ensures precise noise removal while maintaining image integrity [3]. The advent of deep learning has further revolutionnized denoising techniques. The Deep Convolutional Neural Network (SeConvNet) utilizes selective convolutional blocks to effectively reduce SAPN, particularly at high noise densities, showcasing the potential of neural networks in image restoration tasks [5].

Even with these advancement in noise elimination of digital images maintaining the optimal balance between noise reduction and detail preservation across varying noise densities is one of the challenge to researchers.

In this research article the authors have proposed a novel Adaptive Weighted Mean-Median Filter (AWMMF) that dynamically assigns weights to mean and median values within a local window, based on estimated noise density. The AWMMF aims to enhance denoising performance while preserving critical image details, addressing the shortcomings of existing methods. This research article contributes:

- A discussion on the various filtering methods to eliminate the SAPN.
- A discussion on the implementation of AWMMF for SAPN elimination.
- A discussion on the superior effectiveness of AWMMF for SAPN elimination over other filters such as Adaptive Fuzzy Median Filter (AFMF), Fast and Efficient Median Filter (FEMF), DAF, NHF, IAT2FF, RF, SeConvNet, and Adaptive Switching Modified Decision-Based Unsymmetric Trimmed Median Filter (ASMDBUTMF).

The article is structured as follows: Literature review followed by introduction is presented in Section 2. The proposed algorithm of AWMMF is elaborated in Section 3. Results and discussion are presented in Section 4 followed by the Conclusion.

Literature Review

In the field of digital image processing elimination of SAPN is the biggest challenge and many researchers are working on that. From the literature, it is concluded that over the past decade, numerous methodologies have been proposed, including conventional median filtering techniques, and advanced adaptive and hybrid models. In conventional filters like SMF, the value of each pixel is replaced with the median of the intensities within a defined neighborhood. It is more effective for low-noise density however tends to blur the image at higher noise levels. A modified version of SMF is an adaptive Median Filter (AMF) which adjusts window size based on local noise density. AMF can result in excessive smoothing, especially in images with significant noise [6]. Another type of filter used to eliminate SAPN is decision-based and switching filters (DBA). It replaces noisy pixels using neighboring values but may cause artifacts at high noise levels. In its modified version decision-based unsymmetric trimmed median filter the performance is improved by a trimming process in high-noise conditions [7]. Further the performance is enhanced by using adaptive threshold mechanism for detecting noisy pixels in ASMDBUTMF. For restoration, an unsymmetric trimmed median filter is applied. As a result ASMDBUTMF preserves fine anatomical details in MRI images more effectively than DBA [8]. In fuzzy logic based filters fuzzy reasoning is used to determine the level of noise corruption. In AFMF, based on the detected noise level median median filtering is applied to eliminate the noise [9]. Modified version IAT2FF detects noise using an enhanced adaptive type-2 fuzzy noise identifier. Moreover for restoration, it applies a modified ordinary fuzzy logic approach [10]. For High noise densities FEMF was implemented which identifies natural pixels for restoration based on prior information. It does not rely on iterative noise detection. It is ideal for swift processing applications because of its simple logic and rapid execution [11]. Morphological filters analyze the geometric structure of images and combined with statistical methods to improve denoising performance. NHF integrates mathematical morphology operations with a trimmed median filter [12]. Edge-Preserving and Detail-Aware Filters uses the EATV model. Maintains the edge integrity while reducing the noise level by applying the total variation denoising selectively [3, 13]. In regeneration filter high-density SAPN is eliminated by selectively processing noisy pixels. It maintains image integrity by preserving uncorrupted pixels. RF works in two phases: noise identification via adaptive threshold and reconstruction using neighboring pixels [14]. Researchers also used deep learning based approaches to eliminate SAPN. Convolutional Neural Networks (CNN) are trained to distinguish and eliminate noise patterns. Deep CNNs with selective convolutional blocks can efficiently minimize SAPN at high densities. These models perform better by learning intricate mappings from noisy to clean images. However, it requires significant computational resources and extensive training datasets [5].

From the literature, it is concluded that researchers have explored innovative strategies for SAPN removal. A two-step method involving a median-type filter followed by an adaptive non-local bilateral filter has been proposed to address the limitations of traditional filters. This approach effectively weakens median filter errors and preserves image details [13]. Additionally, methods incorporating noise detection strategies with non-convex sparsity regularization have shown promise in accurately identifying and removing noise while maintaining image integrity [15].

The evolution of SAPN removal techniques reflects a balance between noise suppression and detail preservation. Traditional methods offer simplicity and speed; however, they have limitations in maintaining image quality at high noise levels. On the other hand, adaptive, fuzzy logic-based, and deep learning approaches provide enhanced performance but may introduce complexity and computational demands. Ongoing research continues to seek methods that effectively combine efficiency with high-quality denoising outcomes. The authors have proposed the AWMMF for SAPN elimination.

Methodology

From the literature, it is concluded that while elimination of the SAPN at high noise density SMF and AMF have limitations in maintaining the balance between noise reduction and detail preservation. To address these problems authors have proposed AWMMF which dynamically adjusts the filtering process based on local noise density, assigning adaptive weights to the mean and median values within a local window. In this study, the authors have utilized standard grayscale test images of Lena [16]. This image is artificially corrupted with varying densities (10 to 90 %) of SAPN to simulate real-world conditions. The step-by-step procedure of the proposed AWMMF methodology is presented below:

Step 1: Noise Detection. For each pixel in the image, define a sliding window cantered on the current pixel.

Identify whether the current pixel is a noisy or non-noisy candidate from its intensity (minimum or maximum possible value).

Step 2: Adaptive Window Adjustment. If the current pixel is a noise candidate, initialize the window size to a predefined minimum (e.g., 3×3).

Expand the window size incrementally (e.g., to 5×5, 7×7) until a sufficient number of non-noisy pixels are found or a maximum window size is reached.

Step 3: Weight Calculation. Within the determined window, calculate the median (Med) and mean (Mean) of the non-noisy pixels.

Estimate the local noise density (ρ)

$$\rho = \frac{\text{noisy pixels}}{\text{tital number of pixels window}}.$$

Compute the weighting factor (α) based on ρ, where $\alpha = f(\rho)$ is a monotonically increasing function ensuring $0 \le \alpha \le 1$.

Step 4: Pixel Restoration. Replace the noisy pixel's value (P) with a weighted combination of the median and mean:

$$\text{Pnew} = \alpha \times \text{Mean} + (1 - \alpha) \times \text{Med}.$$

If the current pixel is not noisy, retain its original value.

Step 5: Iterative Processing. Repeat the above steps for each pixel in the image until the entire image is processed.

Results and Discussion

In this proposed work the AWMMF algorithm is written in a MATLAB environment and Intel Core i5 processor and 16GB RAM system is used for execution. To analyze the efficacy of the proposed AWMMF standard grayscale test images of Leena are artificially corrupted with varying densities (10 to 90 %) of SAPN to simulate real-world conditions. The performance of the AWMMF has been compared with the seven existing filters AFMF, FEMF, DAF, NHF, RF, IAT2FF, SeConvNet, and ASMDBUTMF for the varying noise densities (10 to 90 %). The performance is compared based on their Peak Signal-to-Noise Ratio (PSNR), Mean Squared Error (MSE), and Structural Similarity Index (SSIM) and the Image Enhancement Factor (IEF). The detail discussion of the each performance parameter is given below.

Peak Signal-to-Noise Ratio (PSNR). PSNR basically indicates the image quality and given by,

$$PSNR = \frac{\text{maximum possible power of a signal}}{\text{power of noise}}. \quad (1)$$

For better noise suppression PSNR of the filter should be high [16]. The results obtained for PSNR of all the filters considered in this study are given in Table 1.

From Table 1 it is clear that AWMMF consistently yields the highest PSNR at every noise level. This demonstrates that it retains image quality better than other methods under increasing noise.

Fig. 1 shows the graph of PSNR for all the filters under study for the noise level 10 to 90. From Fig. 1 it is observed that for the Deep Learning Filters considered for this study i.e. SeConvNet and IAT2FF the PSNR values remain constant and low indicating that they are not well trained or not suitable for the noise level considered for this study. They are not performing well compared to traditional filters and the proposed AWMMF.

PSNR for NHF and RF declined steadily with an increase in noise level. A low value of PSNR indicates that they have poor noise suppression and image restoration. From the graphs, it is found that for lower noise levels (10 to 30) the performance of the proposed AWMMF is similar to FEMF, AFMF, and ASMDBUTMF. However, for higher noise levels the PSNR for other filters decreased considerably compared to AWMMF which proves the superior performance and robustness of the proposed AWMMF at high noise densities.

Table 1

PSNR for filters under study for varying noise density

Noise	AFMF	FEMF	DAF	NHF	RF	IAT2FF	SeConvNet	ASMDBUTMF	AWMMF
10	35.39733	35.90229	31.75012	28.0879	29.76457	15.25033	15.25033	35.90229	**35.94136**
20	31.01415	32.05459	28.12879	22.28446	24.93479	12.21703	12.21703	32.05459	**32.13226**
30	27.71355	30.35453	23.2121	17.5408	21.9033	10.46196	10.46196	30.34921	**30.46994**
40	24.30438	28.91913	18.67052	13.98804	19.52521	9.209097	9.209097	28.87144	**29.08077**
50	21.17886	27.49012	15.01558	11.51263	17.56481	8.23075	8.23075	27.28456	**27.66278**
60	18.52804	26.61401	12.08999	9.713606	15.92049	7.436238	7.436238	25.74744	**26.77853**
70	16.32833	25.67214	9.865479	8.41461	14.53965	6.787401	6.787401	23.48028	**25.81697**
80	14.29431	24.62507	7.955471	7.378486	13.22843	6.201846	6.201846	20.2284	**24.75186**
90	12.50589	23.06581	6.421403	6.494591	12.02737	5.673323	5.673323	16.50731	**23.10802**

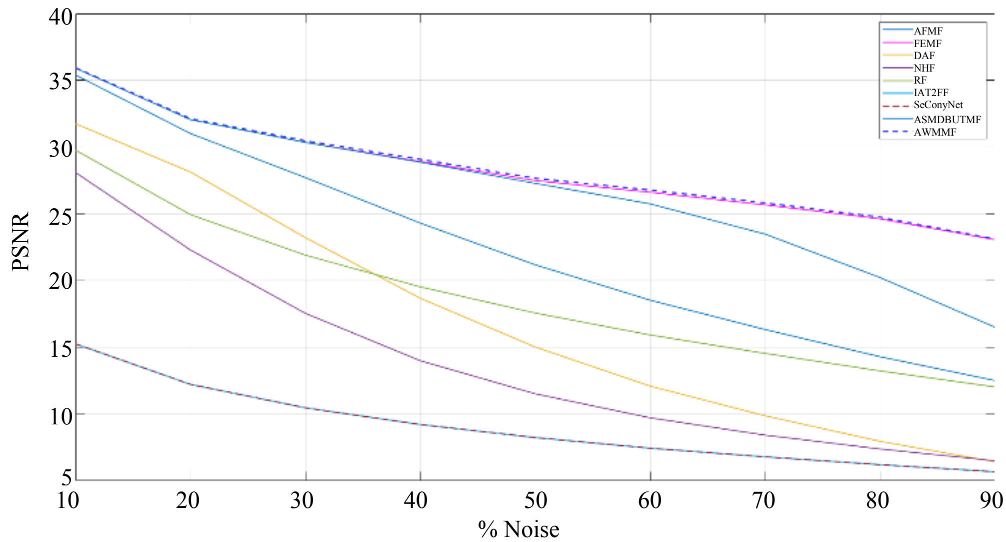

Fig. 1. PSNR for varying noise density

4.2. Mean Squared Error (MSE). MSE indicates the denoising capability of the filter and is given by

$$MSE = \frac{1}{HW}\sum_{i=1}^{H}\sum_{j=1}^{W}(O_{(i,j)} - D_{(i,j)})^2, \qquad (2)$$

where H and W are the height and width of the image respectively.

$O(i, j)$ and $D(i, j)$ are the pixel value of the original and denoised images at position (i, j) respectively.

For superior denoising performance the filters should have minimum MSE [17]. Table 2 presents the MSE for all filters considered for this study at various noise densities. From the Table 2, it is concluded that MSE for AWMMF is the lowest compared to all the filters for all the noise densities proving the accuracy of the proposed AWMMF. Fig. 2 shows the graph of MSE for all filters with varying noise densities.

From Fig. 2 it is observed that MSE for DAF, NHF, IAT2FF, and SeConvNet is highest for all noise densities resulting in the filters being less accurate. AFMF and RF perform moderately below 40 % noise levels however their stability is not strong at higher noise densities. For low noise densities MSE for ASMDBUTMF and FEMF is quite similar to AWMMF but as the noise density increases the MSE also increases drastically compared to the proposed AWMMF.

Table 2

MSE for filters under study for varying noise density

Noise	AFMF	FEMF	DAF	NHF	RF	IAT2FF	SeConvNet	ASMDBUTMF	AWMMF
10	18.76495	16.70517	43.45785	100.9927	68.64732	1941.097	1941.097	16.70517	**16.55559**
20	51.48322	40.51554	100.0463	384.2679	208.7379	3902.813	3902.813	40.51554	**39.79739**
30	110.0843	59.92761	310.3636	1145.514	419.5179	5846.344	5846.344	60.00106	**58.35608**
40	241.3473	83.40019	883.1375	2595.83	725.3691	7801.366	7801.366	84.32107	**80.35318**
50	495.6717	115.896	2048.907	4590.054	1139.199	9772.493	9772.493	121.5135	**111.3787**
60	912.5915	141.8012	4018.665	6945.76	1663.534	11734.28	11734.28	173.1155	**136.5299**
70	1514.424	176.1435	6707.064	9367.406	2286.207	13625.12	13625.12	291.7779	**170.366**
80	2419.077	224.1679	10411.98	11891.37	3091.983	15591.78	15591.78	616.9362	**217.7182**
90	3651.667	320.9955	14823.13	14575.43	4077.023	17609.54	17609.54	1453.28	**317.8909**

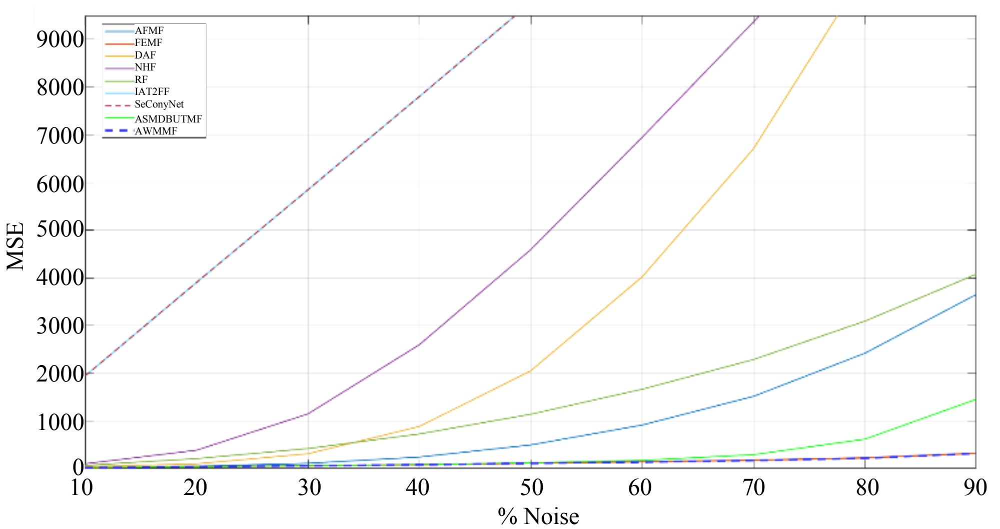

Fig. 2. MSE Comparison of different filters across noise density

Structural Similarity Index (SSIM). SSIM represents the restoration capability of the filters and is given by

$$SSIM(O,\ D) = \frac{(2\mu_O\mu_D + C_1)(2\sigma_{OD} + C_2)}{(\mu_O^2 + \mu_D^2 + C_1)(\sigma_O^2 + \sigma_D^2 + C_2)}, \quad (3)$$

where μ_O, μ_D – mean intensity of original image O and denoised image D respectively; σ_O^2, σ_D^2 – variance of original image O and denoised image D respectively; σ_{OD} – covariance between original image O and denoised image D; C_1, C_2 – small constant to stabilize the division.

The filters with better image restoration quality has SSIM near to unity [17]. Table 3 shows the comparison of SSIM for all filters under study for the varying noise density. From Table 3 it is concluded that SSIM for AWMMF at low noise density is 0.97872 and 0.731431 at highest noise density indicating the consistency of the proposed AWMMF compared to other filters under study.

From Fig. 3 it is found that IAT2FF and SeConvNet are having very low SSIM for all noise density levels. It suggests that these models fail to preserve the image details under SAPN. SSIM for DAF, NHF, and RF decreases with an increase in noise density indicating the poor performance in maintaining the quality of the image. From the graph, it is observed that FEMF and AFMF perform well for the noise densities below 30 % however the SSIM drops down drastically as the noise density increases. The SSIM for ASMDBUTMF and proposed AWMMF is almost equal at low noise densities but it falls to 0.327303 at 90 % noise level for ASMDBUTMF. This proves that the proposed AWMMF preserves the image details at all noise densities.

Table 3

SSIM for filters under study for varying noise density

Noise	AFMF	FEMF	DAF	NHF	RF	IAT2FF	SeConvNet	ASMDBUTMF	AWMMF
10	0.975364	0.978548	0.902207	0.858706	0.791894	0.18369	0.18369	0.978548	**0.97872**
20	0.939636	0.958276	0.852765	0.706201	0.589516	0.090043	0.090043	0.958276	**0.95903**
30	0.861298	0.940857	0.704129	0.466918	0.434423	0.055817	0.055817	0.940685	**0.942549**
40	0.706129	0.921426	0.456839	0.264999	0.3202	0.038711	0.038711	0.919215	**0.924624**
50	0.510069	0.898153	0.236385	0.155046	0.237748	0.027057	0.027057	0.885013	**0.902765**
60	0.330928	0.873117	0.11035	0.089764	0.177746	0.019458	0.019458	0.810986	**0.878218**
70	0.206861	0.842543	0.054127	0.0533	0.130361	0.013836	0.013836	0.683534	**0.847725**
80	0.128468	0.8015	0.02784	0.030233	0.09595	0.010235	0.010235	0.497628	**0.806353**
90	0.074095	0.729509	0.012057	0.01353	0.062018	0.005928	0.005928	0.327303	**0.731431**

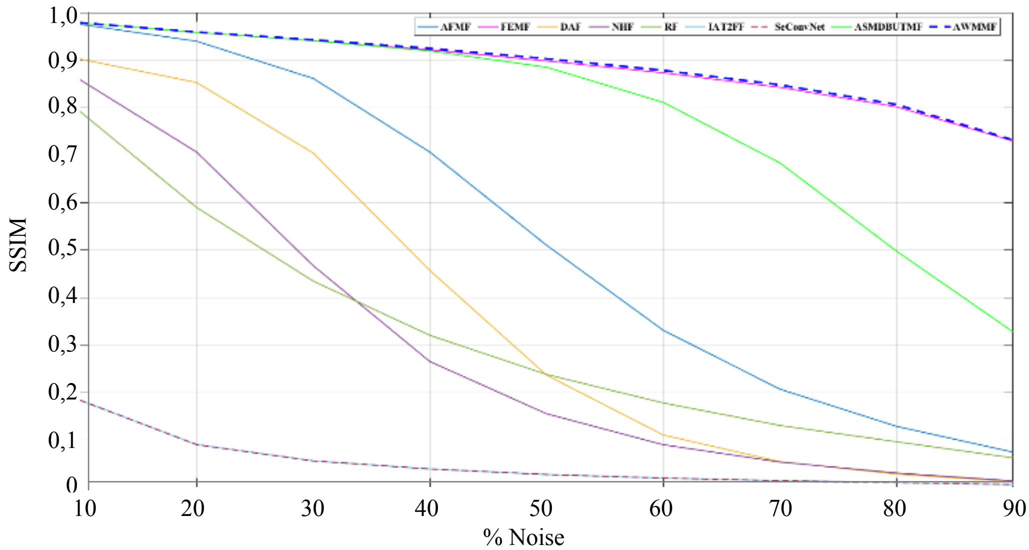

Fig. 3. SSIM of all filters with varying noise density

Image Enhancement Factor (IEF). The efficacy of the image enhancement or restoration algorithm is also evaluated by IEF which is a quantitative metric. The Image Enhancement Factor quantifies how much an enhanced image improves over a noisy or degraded image, in relation to the original image. It is calculated as follows:

$$IEF = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n}(x(i,j)-O(i,j))^2}{\sum_{i=1}^{m}\sum_{j=1}^{n}(f(i,j)-O(i,j))^2}, \quad (4)$$

where $O(i,j)$ is the original image; $x(i,j)$ is the Noisy image; $f(i,j)$ is the filtered image.

Table 4 shows the comparison of IEF for all filters under study for the noise density range from 10 to 90. Higher value of IEF means better enhancement of the image. From the Table 4 it is conclude that for AWMMF the value of IEF is highest for all the noise levels compared to all filters.

Fig. 4 shows the comparison of the graph of IEF of all filters with varying noise densities. From the Fig. 4 it is conclude that in case of traditional filters like NHF and RF for low noise densities image enhancement is good but for higher noise level the image is degraded. On the other hand for IAT2FF, the IEF is constant 1 for all noise densities which means that the image enhancement is negligible. While comparing the IEF value for SeConvNet it is observed that it is consistently remain below 2, indicating either inadequate generalization, inefficient training, or restricted tolerance to salt-and-pepper noise in this particular situation. At low noise level AFMF and ASMDBUTMF performs well however with increase in the noise level the IEF value decreases. The FEMF and AWMMF perform similarly, while the AWMMF has the greater IEF.

Table 4

IEF for filters under study for varying noise density

Noise	AFMF	FEMF	DAF	NHF	RF	IAT2FF	SeConvNet	ASMDBUTMF	AWMMF
10	98.86405	113.8041	43.61288	18.39216	27.9361	1	0.913798	113.8041	**114.7465**
20	81.71998	107.0806	39.70718	10.50791	18.98984	1	1.39623	107.0806	**108.9917**
30	52.08079	96.79249	18.56904	5.099624	13.90591	1	1.715288	96.72941	**99.77455**
40	33.54832	93.31618	9.127153	3.087682	10.8069	1	1.875194	92.69405	**96.74793**
50	20.40314	84.99859	4.892097	2.182304	8.696367	1	2.08473	81.42757	**88.56061**
60	12.88907	83.06283	2.933908	1.694546	7.038211	1	1.569965	68.16943	**86.52421**
70	8.93947	78.02919	2.012163	1.453138	5.924151	1	1.759722	45.86859	**80.70468**
80	6.455024	68.19781	1.5037	1.31052	5.049117	1	1.901367	25.10251	**70.12437**
90	4.850621	53.51262	1.193024	1.210347	4.341645	1	1.848439	12.11493	**54.10665**

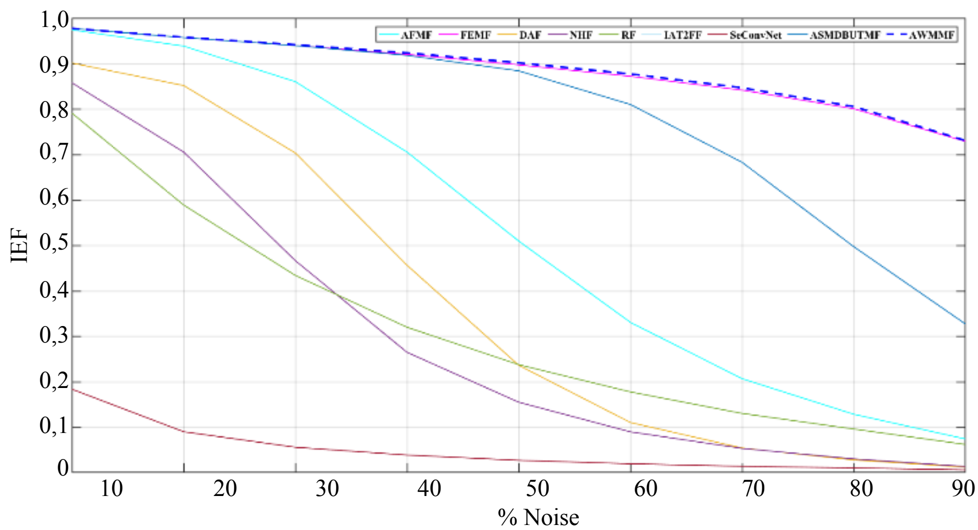

Fig. 4. IEF of all filters with varying noise density

Fig. 5 shows the input image, noisy image, and output images of all the filters considered for this study with various noise densities. From Fig. 4 it is observed that Traditional filters (AFMF, FEMF) perform well at low noise and perform poorly at high noise. DAF, NHF, and RF perform poorly at even medium noise with lots of blurring. For IAT2FF, SeConvNet the performance is very poor at all noise levels. ASMDBUTMF performs decent to moderate noise levels but the performance is degraded at high noise levels. The proposed AWMMF performs well at all noise levels.

From the above comparative analysis for various parameters of all the filters, it is clear that the proposed AWMMF outperforms traditional denoising methods across various noise densities. The adaptive weighting mechanism allows AWMMF to effectively balance noise reduction and detail preservation. While SMF and AMF are effective at lower noise densities, their performance degrades significantly as noise density increases.

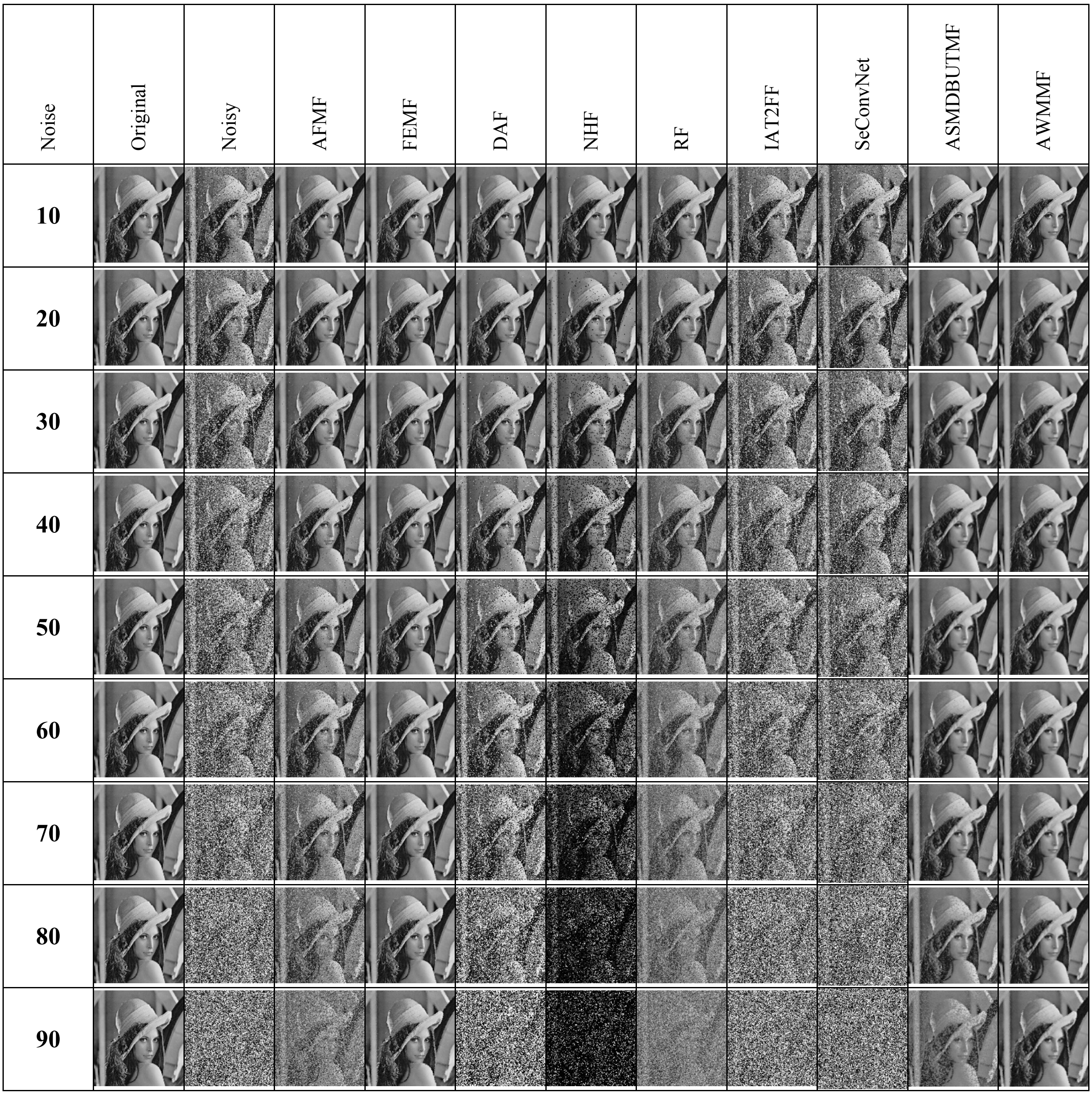

Fig. 5. Visual performance of AWMMF compared to other filters under study

DBA shows improved performance over SMF and AMF but still falls short compared to AWMMF, especially at higher noise levels. The superior performance of AWMMF can be attributed to its adaptive nature, which adjusts the filtering parameters based on local noise characterristics. This adaptability enables AWMMF to maintain high image quality even under challenging conditions. The AWMMF offers several advantages over conventional filters such as adaptive nature of the filter effectively handles varying noise densities. It maintain the balance between noise reduction and image detail Preservation because of use of mean and median values. The iterative approach and dynamic adjustments make the filter robust against high-density noise scenarios, where traditional filters often fail.

Conclusion

In this article, we have proposed the AWMMF filtering for eliminating the SAPN effectively noise in digital images. Moreover, the PSNR, MSE, and SSIM of AWMMF compared with the seven state-of-the-art filters using the benchmark Leena image at varying noise density from 10% to 90%. From the comparative analysis it is found that the AWMMF ensured superior noise reduction while maintaining image details, making it a robust and efficient choice for image restoration tasks.

The novelity of Key findings include as following:

- AWMMF consistently achieved higher PSNR values and lower MSE across all noise densities.
- The proposed AWMMF exhibited superior SSIM performance, indicating better structural preservation and visual quality.
- Unlike conventional methods, AWMMF dynamically adjusted its filtering strategy based on local noise density, providing enhanced adaptability to varying noise levels.

These results highlight AWMMF's effectiveness in medical imaging, remote sensing, and surveillance, where high-quality image restoration is critical. The future work could integrate AWMMF with deep learning models to enhance the performance and explore the effectiveness of AWMMF with other types of noises such as Gaussian, speckle, and Poisson noise, expanding its versatility across imaging domains.

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known conflict of interest that could have appeared to influence the work reported in this paper.

Nomenclature

AWMMF	Adaptive Weighted Mean-Median Filter
SMF	Standard Median Filter
AMF	Adaptive Median Filter
RF	Regeneration Filter
NHF	Nonlinear Hybrid Filter
EATV	Edge-Adaptive Total Variation
DAF	Detail-Aware Filter
AFMF	Adaptive Fuzzy Median Filter
IAT2FF	Improved Adaptive Type-2 Fuzzy Filter
SeConvNet	Deep Convolutional Neural Network
FEMF	Fast and Efficient Median Filter
ASMDBUTMF	Adaptive Switching Modified Decision-Based Unsymmetric Trimmed Median Filter
PSNR	Peak Signal-to-Noise Ratio
MSE	Mean Squared Error
SSIM	Structural Similarity Index
IEF	Image Enhancement Factor

REFERENCES

1. Erkan U., Kilicman A. (2016) Two new Methods for Removing Salt-And-Pepper Noise From Digital Images. *ScienceAsia,* 42 (1), 28–32, 2016.
2. 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), 1709. https://doi.org/10.3390/diagnostics13101709.
3. 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. https://doi.org/10.3389/ fams. 2022.918357.
4. Mohan S., Paulchamy B. (2024) Removal of Salt and Pepper Noise Using Adaptive Switching Modified Decision-Based Unsymmetric Trimmed Median Filter Optimized with Hyb-BCO-FBIA. *Automatika,* 65 (3), 852–865. https://doi.org/10.1080/00051144.2024.2321807.

5. Rafiee A. A., Farhang M. (2023) A Deep Convolutional Neural Network for Salt-and-Pepper Noise Removal Using Selective Convolutional Blocks. *Applied Soft Computing*, 145, 110535. https://doi.org/10.1016/j.asoc.2023.110535.
6. Hwang H., Haddad R. A. (1995) Adaptive Median Filters: New Algorithms and Results. *IEEE Transactions on Image Processing*, 4 (4), 499–502. https://doi.org/10.1109/83. 370679.
7. Esakkirajan S., Veerakumar T., Subramanyam A. N., PremChand C. H. (2011) Removal of High Density Salt and Pepper Noise Through Modified Decision Based Unsymmetric Trimmed Median Filter. *IEEE Signal Processing Letters*, 18 (5), 287–290. https://doi.org/10.1109/lsp.2011.2122333.
8. Sheela C. J. J., Suganthi G. (2020) An Efficient Denoising of Impulse Noise From MRI Using Adaptive Switching Modified Decision Based Unsymmetric Trimmed Median Filter. *Biomedical Signal Processing and Control,* 55, 101657. https://doi.org/10.1016/j.bspc.2019.101657.
9. Toh K. K. V., Isa N. A. M. (2010) Noise Adaptive Fuzzy Switching Median Filter for Salt-and-Pepper Noise Reduction. *IEEE Signal Processing Letters*, 17 (3), 281–284. https://doi.org/10.1109/lsp.2009.2038769.
10. Singh V., Agrawal P., Sharma T., Verma N. K. (2022) Improved Adaptive type-2 Fuzzy Filter with Exclusively Two Fuzzy Membership Function for Filtering Salt and Pepper Noise. *Multimedia Tools and Applications*, 82 (13), 20015–20037. https://doi.org/10.1007/s11042-022-14248-2.
11. Hsieh M.-H., Cheng F.-C., Shie M.-C., Ruan, S.-J. (2013) Fast and Efficient Median Filter for Removing 1–99 % Levels of Salt-and-Pepper Noise in Images. *Engineering Applications of Artificial Intelligence*, 26 (4), 1333–1338. https://doi.org/10.1016/j.engappai.2012.10.012.
12. Irum I., Sharif M., Raza, M., Mohsin S. (2015) A Non-linear Hybrid Filter for Salt & Pepper Noise Removal from Color Images. *Journal of Applied Research and Technology*, 13(1), 79–85. https://doi.org/10.1016/s1665-6423(15)30015-8.
13. Liang H., Li N., Zhao S. (2021) Salt and Pepper Noise Removal Method Based on a Detail-Aware Filter. *Symmetry*, 13 (3), 515. https://doi.org/10.3390/sym13030515.
14. Ivković R. M., Milošević I. M., Milivojević, Z. N. (2024) Regeneration Filter: Enhancing Mosaic Algorithm for Near Salt & Pepper Noise Reduction, *Sensors,* vol. 25, No 1, 1–22. https://doi.org/10.20944/preprints202411.0737.v1.
15. Chen Y., Huang Y., Wang L., Huang H., Song J., Yu C., Xu Y. (2022) Salt and Pepper Noise Removal Method Based on Stationary Framelet Transform with Non-Convex Sparsity Regularization. *IET Image Processing*, 16 (7), 1846–1865. https://doi.org/10.1049/ipr2.12451.
16. Gonzalez R. C., Woods R. E. (2018) *Digital Image Processing.* 4th ed. Pearson.
17. Zhou Wang, Bovik A. C., Sheikh H. R., Simoncelli E. P. (2004) Image Quality Assessment: From Error Visibility to Structural Similarity. *IEEE Transactions on Image Processing*, 13 (4), 600–612. https://doi.org/10.1109/tip.2003.819861.

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