Journal of Information System and Technology Management
JISTM
EISSN: 0128-1666
Volume 10 Issue 38 (March 2025) PP. 23-39
DOI: 10.35631/JISTM.1038003

JOURNAL OF INFORMATION SYSTEM AND TECHNOLOGY MANAGEMENT (JISTM)
www.jistm.com

GLOBAL ACADEMIC EXCELLENCE

ELIMINATING HIGH DENSITY SALT AND PEPPER NOISE FROM GRAYSCALE IMAGE USING ALPHA TRIMMED MEAN-MEDIAN FILTER

Mohd Saifunnaim Mat Zain[1*], Ahmad Kadri Junoh[2]

[1] Bahagian Kawalan Kualiti Latihan, Institut Latihan Perindustrian Jitra, Kedah, Malaysia
Email: naimkn@gmail.com
[2] Institute Engineering Mathematics, Universiti Malaysia Perlis, Arau, Perlis, Malaysia
Email: kadri@unimap.edu.my
[*] Corresponding Author

Article Info:

Article history:
Received date: 25.11.2024
Revised date: 16.12.2024
Accepted date: 30.01.2025
Published date: 04.03.2025

To cite this document:

Mat Zain, M. S., & Junoh, A. K. (2025). Eliminating High Density Salt And Pepper Noise From Grayscale Image Using Alpha Trimmed Mean-Median Filter. *Journal of Information System and Technology Management, 10* (38), 23-39.

DOI: 10.35631/JISTM.1038003

Abstract:

The use of images has increased over the previous decade, and they have the potential to be effective communication tools, similar to social media. In social media, uploading visual information or images seems to be becoming more popular. The appearance of noise disturbs the original information in the image. Thus, removing the noise before using the image for subsequent tasks is necessary. The approaches for image restoration are based on a mathematical model of image deterioration. Alpha trimmed mean median filter (ATMMF) is proposed as a new method for removing salt and pepper noise in digital images. The basic principle behind this method is that it starts with noise detection and then moves on to a filtering strategy. The experimental process was performed with 12 samples of grayscale images with a variable salt and pepper noise density ranging from 10% to 90% to compare the proposed method to other widely used methods. Afterward, PSNR and SSIM were taken as the quality measurements. The proposed filtering technique is simple to use and implement. Experimental results show that the proposed method has successfully reduced salt and pepper noise in high noise density. It outranks all the previous filtering methods regarding visual effects and quantitative measure results.

Keywords:

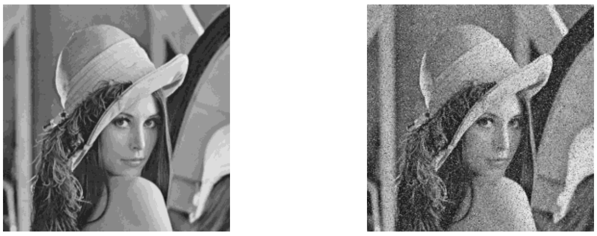
Noise; Salt And Pepper Noise; Image Restoration; Mean Filter; Median Filter; Alpha Trimmed Mean-Median Filter; Grayscale Image Single Spacing

Journal of Information System and Technology Management
JISTM
EISSN: 0128-1666
Volume 10 Issue 38 (March 2025) PP. 23-39
DOI: 10.35631/JISTM.1038003

Introduction

Images can be expressed considerably faster than words by humans. In addition, images provide richness and perspective to a description or tale. We can open a page and immediately see and understand the image rather than reading text that needs to scan, process and understand the words. An image may be defined as a two-dimensional function and needs data sources to be understood and analysed by many applications. Images are often contaminated by noise, producing low-quality images during image acquisition and transmission. Besides, noise causes artefacts, false edges, invisible lines, corners, and fuzzy objects, as well as disrupting background sceneries.

The word noise refers to any undesirable and/or random occurrence that might damage a picture by distorting its original information and complicating any pre-processing. Salt-and-pepper noise is also called shot noise, random noise, independent noise or spike noise. The pixels in the image of salt and pepper noise are highly varied in colour or unlike the pixels around them in terms of intensity. Sharp and abrupt disturbances in the image signal might induce salt and pepper deterioration. The corrupted pixels take a salt value of 255 at the gray level or a pepper value of 0 at the gray level. Black and white dots will appear randomly on the picture when viewed, hence the term salt and pepper noise. Figure 1. shows the image with salt and pepper noise.



(a) **(b)**

Fig. 1. Lena image (a) Original image (b) Salt and pepper noise image

Thus, removing the noise before using the image for subsequent tasks is necessary. The effectiveness of a noise reduction procedure in an image is a critical consideration. The image restoration is not only to remove noise but also to preserve the edge and texture details. Many image restoration methods exist because of the requirement for noiseless and well-defined images for improved clarification and analysis. The approaches for image restoration are based on mathematical and statistical models of image deterioration. Meanwhile, image denoising, noise removal or noise reduction can also be called image restoration, originally shown by Wiener and Kolmogorov in the 1940s.

Generally, filtering is the process of restoring a corrupted image to its original state by removing unwanted noise. It has been made to reduce noise while keeping as many image details and structures as possible. There are a variety of filtering techniques that come from various disciplines. The median filter (MF) is one of the non-linear processes for reducing grey or salt and pepper noise and preserving an image's edge. However, it provides a weak filtering result for small size or high density of noise by removing some important information from the image. A Standard Median Filter (SMF) is the basic model of this filter, and it treats all the pixels of the image equally, whether the image is corrupted or uncorrupted. Then, a Weighted Median Filter (WMF) was proposed by Brownrigg to overcome this drawback by reducing the smoothing effect, preserving image sharpness, and treating all pixels. A Progressive median

Journal of Information System and Technology Management
JISTM
EISSN: 0128-1666
Volume 10 Issue 38 (March 2025) PP. 23-39
DOI: 10.35631/JISTM.1038003
filter (PSMF) is more effective for high noise density. However, the noise detection accuracy is limited.

Hence, several other filters derived from the median filter have been proposed to address their shortcomings through improvisations and novel ideas such as The tri-states median filter, modified directional weighted median filter, recursive weighted median filter and multi-state median filter. Dong & Xu also stated that in the selected window, the directional weighted median filter (DWMF) calculates the total absolute differences between the pixel values of the grey scale in four directions. The directional weighted median filter (DWMF) described corrects the centre pixel of a 7 7 sliding window by checking if its value is 0 or 255, indicating it is noisy. However, the filtering causes images to become blurry, leave black and white marks, and become more complex during the high computational filtering process.

In addition, Adaptive Median Filter (AMF) is a better version of the Standard Median Filter (SMF) compatible with various window sizes. Adaptive Median Filter (AMF) uses a threshold to compare each pixel to its neighbours, with the threshold and the neighbourhood size being variables that can be changed. AMF is ineffective because fine details and edges are lost after filtering. The leading cause of this issue is the denoising process's undeliberate replacement of non-noise pixels. Chan claims that their results are superior to those obtained using either the progressive median filter (PSMF), the multi states median filter (MSMF), the noise adaptive soft switching median filter (NASMF), the directional-difference based switching median filter (DDBSMF), or impulse detector switching median filters (ISMF).

A new filtering method was proposed by using decision based median filters known as decision base unsymmetrical median filter (DBUTMF), find the damaged pixel in the chosen window and replace it with the median value of the window, whose dimensions are related to the level of noise. A few adjustments on decision-based filters were proposed by Srinivasan & Ebenezer They are current-based decision Algorithm (NEDBF) that either uses the median pixel or the neighborhood pixel to replace the noisy pixels. Although the NEDBF produces good results, it lacks a smooth transition between pixels caused by the flashing effect, resulting in unclean and tainted edges in the output image. The flashing effect is caused by the frequent substitution of neighbouring pixels. To counteract the flashing effect, another example of a decision-based algorithm is a modified decision-based unsymmetric trimmed median filter (MDBUTMF), which was introduced to enhance visual quality but could not restore local characteristics like blurring in the image. The main disadvantage of using a switching median or decision-based filter is that the weighted median value in the specified window's neighbourhood replaces the corrupted pixel in the window's centre, which ignores local characteristics like edges. As a result, the edges, such as local features, are not satisfactorily restored.

Methodology

In general, this research has three phases to the filtering process. Figure 2 describes the flow chart of the filtering method. The first stage adds salt and pepper noise to create a noisy image with a variable noise density ranging from 50% to 90% to the original image (input image) for testing the proposed filtering. The purpose of creating a noise image is to control and change the amount of noise to evaluate the filter's performance under different noise density levels. The original image (input image) used as a benchmark often used in image processing is taken from The USC-SIPI Image Database and ImageProcessingPlace.com.

Journal of Information System and Technology Management
JISTM
EISSN: 0128-1666
Volume 10 Issue 38 (March 2025) PP. 23-39
DOI: 10.35631/JISTM.1038003

A new filtering method, a combination concept of SVD, ATMF and MF, was proposed, namely SVD-ATMMF. This filtering method aims to remove salt and pepper noise as much as possible to produce a high-quality image, both visually and quantitatively. The proposed image filtering procedure will use a 3 x 3 template. Fig 3 shows the twelve gray-scale images sampling with 512 x 512 resolution used to test the performance of the proposed filtering method, which are Cameraman, Castle, Barbara, Lake, Lena, Mandril, Women Blonde, Boats, Bridge, Living Room, Pirate and Gold Hill. The experimental process was performed with these sample images with a variable salt and pepper noise density ranging from 10% to 90%. Afterwards, The PSNR was taken to measure the performance of the proposed filtering method.

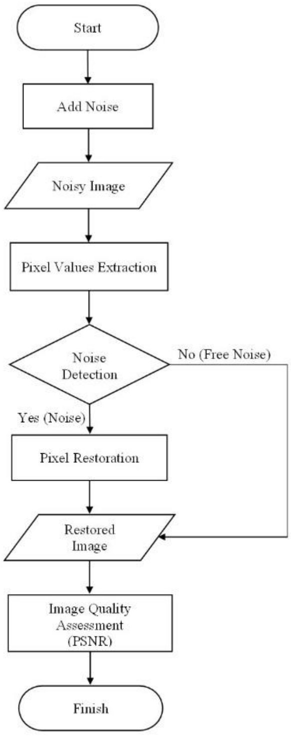


Fig. 2. Flow Chart Of Image Filtering Technique

Journal of Information System and Technology Management
JISTM
EISSN: 0128-1666
Volume 10 Issue 38 (March 2025) PP. 23-39
DOI: 10.35631/JISTM.1038003

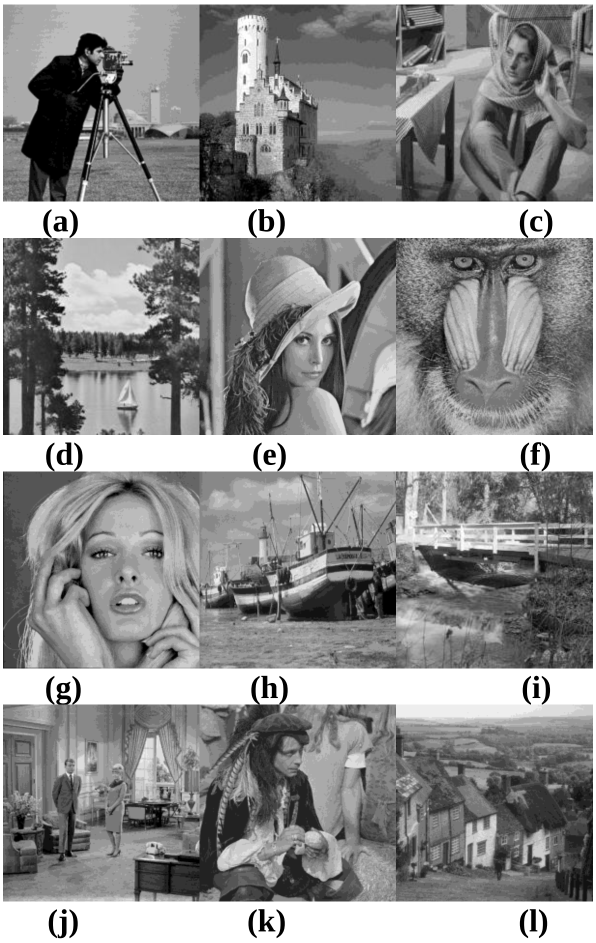


Fig. 3. Twelve sample images (a) Cameraman (b) Castle (c) Barbara (d) Lake (e) Lena (f) Mandril (g) Women Blonde (h) Boats (i) Bridge (j) Living Room (k) Pirates (l) Gold Hill

Noise Detection

Noise detection is where corrupted pixels must be distinguished from uncorrupted pixels based on SVD. This is very important to enable the replacement process only on the corrupted pixel. SVD is a method of factoring a matrix (A) into three matrices consisting of a diagonal matrix (S) and two orthonormal matrices (U and V), $A_{mxn} = U_{mxm}S_{mxn}V^T{}_{nxn}$ matrix. A 3 x 3 matrix of SVD will be used in this study as follows eq. (1).

$$\underbrace{\begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix}}_{A} = \underbrace{\begin{bmatrix} u_{11} & u_{12} & u_{13} \\ u_{21} & u_{22} & u_{23} \\ u_{31} & u_{32} & u_{33} \end{bmatrix}}_{U} . \underbrace{\begin{bmatrix} s_{11} & 0 & 0 \\ 0 & s_{22} & 0 \\ 0 & 0 & s_{33} \end{bmatrix}}_{S} . \underbrace{\begin{bmatrix} v_{11} & v_{12} & v_{13} \\ v_{21} & v_{22} & v_{23} \\ v_{31} & v_{32} & v_{32} \end{bmatrix}}_{V^T} \quad (1)$$

The diagonal matrix, S from SVD plays important role in noise detection. Matrix S contain singular values that known as S_{11}, S_{22} and S_{33} for 3 x 3 matrix as shown in eq. (2). Singular values are arranged sequentially from the largest to the smallest values on diagonal entries of matrix S [29].

Journal of Information System and Technology Management
EISSN: 0128-1666 JISTM
Volume 10 Issue 38 (March 2025) PP. 23-39
DOI: 10.35631/JISTM.1038003

$$S_{3\,x\,3} = \begin{bmatrix} s_{11} & 0 & 0 \\ 0 & s_{22} & 0 \\ 0 & 0 & s_{33} \end{bmatrix} \quad (2)$$

The diagonal matrix is in charge of entries in matrix A. The entries of diagonal matrix S reveal the variety of distribution values in matrix A. Thus, changes in the distribution of values in matrix A impact entries in the diagonal matrix, S. Compared to other entries, the entry value of S_{22} is susceptible to the value change in matrix A. Furthermore, S_{22} be the second row entry and the second column of the diagonal matrix. S_{22} will be used as an indicator to assess the existence of noise on any 3 x 3 template based on the following inequality eq. (3):

$$\alpha_1 < S_{22} < \alpha_2 \quad (3)$$

Where α_1 is the lower limit and α_2 is the upper limit. Abdurrazzaq et al [30]stated that the value of α_1 value had been set as 3 and the value of α_2 has been set as 8 after doing an experimental quantitative analysis based on the presence of significant colour change in the 3 × 3 templates.

Image Filtering

A noise filtering technique is presented to remove salt and pepper noise from corrupted images while preserving image details. This filtering technique is based on ATMF, which is the windowed filter of non-linear class in the spatial filtering domain and the special case of the order-statistics filter. The basic concept behind this filter is to order the elements within a filtering window, delete elements at the beginning with the lowest intensity (gray) level and end of the ordered set with the highest intensity (gray) level. Then calculate the average value or mean value using the remaining neighbouring pixels.

The centre pixel within the filter window, $\hat{f}(x,y)$, is grey value where x and y are pixel coordinates. gr (s,t) correspond to the remaining mn-α pixels after eliminating the highest of α/2 and the lowest of α/2 values of g(s,t), illustrated in Figure 4. The parameter alpha in the filter is the number of trimmed elements. The ATMF algorithm is given as follows eq. (4):

$$\hat{f}(x,y) = \frac{1}{mn-d} \sum_{(s,t)\varepsilon S_{xy}} g_r\,(s,t) \quad (4)$$

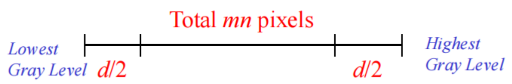


Fig. 4. Trimmed Elements At The Beginning And At The End Of The Ordered Set

The value of α can be anything between zero and mn-1. ATMF becomes an arithmetic mean filter when d is equal to zero. Then, ATMF becomes a median filter when α equal to mn-1. Thus, the parameter, α has a significant impact on the performance of the algorithm. The parameter, α should not be too small when the noise is salt and pepper noise. The calculation process for the ATMF method can be seen in Figure 5. The algorithm of the ATMF is as follows.

a) Place a window of 3 x 3 template over element.
b) Pick up elements.
c) Order elements with ascending sequence intensity (gray) level.

Journal of Information System and Technology Management
EISSN: 0128-1666
JISTM
Volume 10 Issue 38 (March 2025) PP. 23-39
DOI: 10.35631/JISTM.1038003

d) Trimmed the elements at the beginning and end of the given sorted set.
e) Calculate an average by adding together the remaining elements and dividing the total by the number of them.

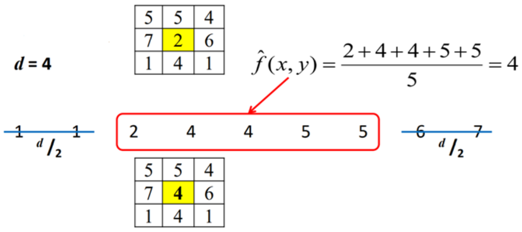


Fig. 5. Process for the ATMF

Then, the filtering process is continued using MF. As mentioned before, the brightness of neighbouring pixels is used to rank them (intensity) and its value is replaced with the median value of the 3 x 3 window template. For example, assume that the pixel values within a window are 10, 3, 4, 9, 5, 12, 6, 7 and 15, and that the pixel being processed is 5. The current pixel location's result from the median filter is 7, the median of the nine values. Figure 6 shows the calculation process for the MF method.

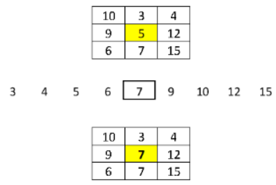


Fig. 6. Process for the MF

Filter Performance

The performance of filtering algorithm is evaluated quantitatively and qualitatively. The Peak Signal to Noise Ratio (PSNR) is a quantitative measure of filtering performance and the difference between the noisy image and the original image. PSNR value is defined by (5) via MSE is the mean square error as follows in (6).

$$\mathrm{PSNR} = 10\log_{10}\left(\frac{255^2}{MSE}\right) \tag{5}$$

$$\mathrm{MSE} = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{i=0}^{n-1}|f(i,j) - g(i.j)|^2 \tag{6}$$

where $f(i,j)$ and $g(i,j)$ represents original and the restored image of the corrupted image. m and n are the image size.

The SSIM is a model that is based on perception. SSIM calculates how good photos and videos appear to people. It compares the original and restored images to determine how similar they are. The formula of SSIM is computed as follows

$$\mathrm{SSIM} = \frac{(2\mu_x\mu_y + C_1) + (2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1) + (\sigma_x^2 + \sigma_y^2 + C_2)} \tag{7}$$

Journal of Information System and Technology Management
JISTM
EISSN: 0128-1666
Volume 10 Issue 38 (March 2025) PP. 23-39
DOI: 10.35631/JISTM.1038003

where μ_x (σ_x) is the average intensities (standard deviation) value in x direction and μ_y (σ_y) is the average intensities (standard deviation) value in y direction. Additionally, C_1 and C_2 are constants that keep the SSIM value at one. This is a grayscale image performance metric that is mathematically defined but does not include a model of the human visual system. To compare the original image with the restored image, this measure takes into account the three primary features of the images: contrast, brightness, and structure.

Results

This section presents the result from a new filtering method, which is a combination concept of SVD, ATMF and MF, namely SVD-ATMMF. This filtering method aims to remove salt and pepper noise as much as possible to produce a high-quality image, both visually and quantitatively. The proposed image filtering procedure will be carried out using a 3 x 3 template for twelve image sampling or benchmark image with 512 x 512 resolution used to test the performance of the proposed filtering method. The images are Cameraman, Castle, Barbara, Lake, Lena, Mandril, Women Blonde, Boats, Bridge, Living Room, Pirate and Gold Hill. These twelve image samples were compared with other studies using the same number of images. Comparison should be made with the same methods, conditions and characteristics as previous methods to determine the effectiveness of the proposed method. The experimental process was performed with these sample images with a variable salt and pepper noise density ranging from 10% to 90%. Afterwards, the primary or raw image will be used to determine whether the proposed method effectively removes salt and pepper noise. Then, the MSE and PSNR were taken as the performance measure like in previous studies to determine the ideal trimming parameter, α as well as the filtering method.

Meanwhile, this section contains the result of different value trimming parameters, α, for ATMF. Cameraman images with different salt and pepper noise densities have been used in finding the best trimming parameter. The result of MSE is presented quantitatively in Table 1 and Figure 7 and for PNSR in Table 2 and Figure 8.

Table 1 The MSE Value Of Different Trimming Parameter

Noise Density	Quality Metrics	Trimming Parameter		
		$\alpha = 2$	$\alpha = 4$	$\alpha = 6$
10%	MSE	31.34	16.85	13.43
20%	MSE	58.20	33.56	21.77
30%	MSE	76.12	52.65	35.22
40%	MSE	86.85	66.84	48.99
50%	MSE	93.42	77.39	60.36
60%	MSE	97.25	84.88	68.95
70%	MSE	99.9	90.65	75.71
80%	MSE	101.54	94.42	80.44
90%	MSE	103.13	97.72	85.29

Journal of Information System and Technology Management
JISTM
EISSN: 0128-1666
Volume 10 Issue 38 (March 2025) PP. 23-39
DOI: 10.35631/JISTM.1038003

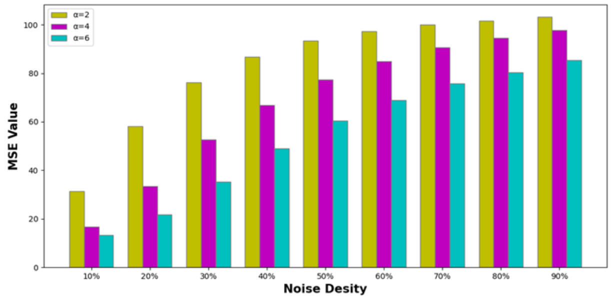


Fig. 7. Graph of the MSE Value Of The Different Value of α

Table 2 The PSNR Value Of Different Trimming Parameter

Noise Density	**Quality Metrics**	**Trimming Parameter**		
		α **= 2**	α **= 4**	α**= 6**
10%	PSNR	33.17	35.87	36.85
20%	PSNR	30.48	32.87	34.75
30%	PSNR	29.32	30.92	32.66
40%	PSNR	28.74	29.88	31.23
50%	PSNR	28.43	29.24	30.32
60%	PSNR	28.25	28.84	29.75
70%	PSNR	28.14	28.55	29.34
80%	PSNR	28.06	28.38	29.00
90%	PSNR	27.99	28.23	28.82

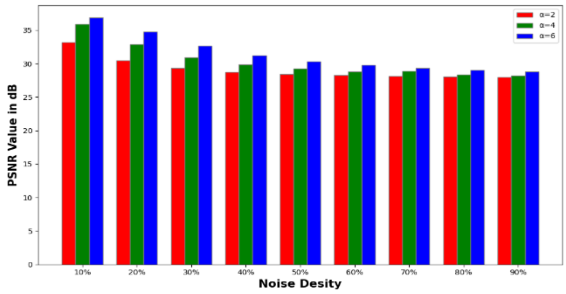


Fig. 8. Graph of the PSNR Value Of The Different Value of α

According to Table 1 and Table 2, it can be seen that the performance of the proposed filtering method becomes better as the value of trimming parameter, α increases in terms of MSE and PSNR value. Figure 7 and Figure 8 illustrate a graphical comparison of MSE and PSNR values for various trimming parameters. Based on the graph, the value of MSE decreases proportionally with the value of d while PSNR increases proportionally with the value of α. Thus, image restoration is better when the MSE is lower and higher PSNR indicates that the filtered method works well in filtering salt and pepper noise images. Other than that, Figure 9 shows some of the filtering images to compare results subjectively. It can be seen clearly that salt (white dot) and pepper (black dot) noise are decreasing when the value of α is increasing. The parameter, α should not be too small when the noise is salt and pepper noise. It will work the same way as the mean filter and have the same drawbacks. As a result, based on all the data in Table 1 and
Table **2**, the value of trimming parameter, α, which is 6, will be used in this study.

Journal of Information System and Technology Management
JISTM
EISSN: 0128-1666
Volume 10 Issue 38 (March 2025) PP. 23-39
DOI: 10.35631/JISTM.1038003

Noise Density	Trimming Parameter		
	α = 2	α = 4	α= 6
10%			
30%			
50%			
70%			
90%			

Fig. 9. Filtering Image Using The Cameraman Image With Three Different Trimming Parameter

Journal of Information System and Technology Management
JISTM
EISSN: 0128-1666
Volume 10 Issue 38 (March 2025) PP. 23-39
DOI: 10.35631/JISTM.1038003

10%

30%

50%

70%

90%

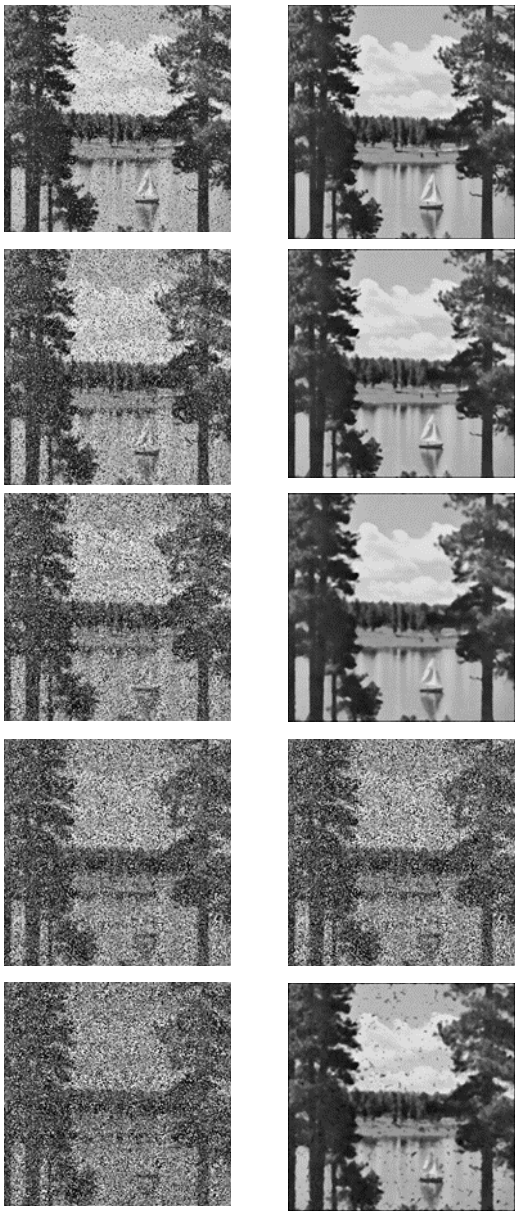


Fig. 10. Performance Of Proposed Filtering Result For Lake Image: (Left) Noisy Image With 10% - 90% Salt And Pepper Noise, (Right) Restored Images

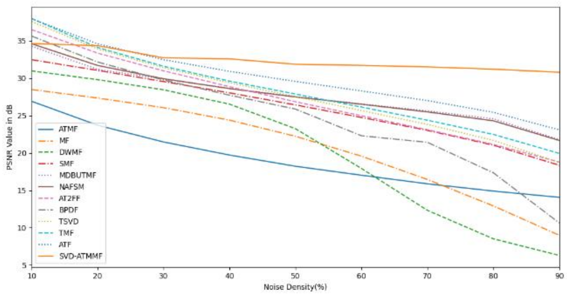


Fig. 11. Graph of PSNR Average Value Of The Sample Images

Journal of Information System and Technology Management
JISTM
EISSN: 0128-1666
Volume 10 Issue 38 (March 2025) PP. 23-39
DOI: 10.35631/JISTM.1038003

Table 3 Comparison of PSNR Average Values For Various Filtering Methods

Noise Density		10%	20%	30%	40%	50%	60%	70%	80%	90%
Previous Methods	**ATMF**	26.9	23.7	21.5	19.7	18.2	17.0	15.9	14.9	14.1
	MF	28.5	27.4	26.1	24.4	22.2	19.6	16.5	12.9	9.0
	DWMF	31.0	29.8	28.5	26.5	23.2	17.9	12.3	8.5	6.3
	SMF	32.5	31.1	29.6	28.0	26.4	24.8	23.0	21.0	18.4
	MDBUTMF	34.3	31.2	29.9	28.6	27.5	26.6	25.6	24.6	21.8
	NAFSM	34.6	31.7	29.9	28.6	27.5	26.5	25.5	24.3	21.7
	AT2FF	36.5	33.4	31.0	28.9	26.9	25.0	23.1	21.2	18.8
	BPDF	35.6	32.2	29.8	27.7	25.9	22.3	21.4	17.3	10.6
	TSVD	37.6	33.9	31.4	29.4	27.5	25.7	23.8	21.7	18.7
	TMF	38.0	34.1	31.6	29.6	27.9	26.1	24.4	22.5	19.9
	ATF	38.0	34.6	32.5	30.9	29.6	28.3	27.0	25.4	23.1
	SVD-ATMMF	34.6	34.4	32.7	32.6	31.9	31.7	31.5	31.2	30.8

Table 4 Comparison of SSIM Average Values For Various Filtering Methods

Noise Density		10%	20%	30%	40%	50%	60%	70%	80%	90%
Previous Methods	**ATMF**	0.78	0.69	0.63	0.58	0.52	0.45	0.36	0.22	0.09
	MF	0.82	0.80	0.76	0.71	0.64	0.52	0.37	0.19	0.06
	DWMF	0.91	0.86	0.81	0.74	0.63	0.42	0.15	0.03	0.01
	SMF	0.92	0.91	0.89	0.86	0.82	0.77	0.70	0.60	0.47
	MDBUTMF	0.97	0.92	0.91	0.89	0.85	0.81	0.77	0.71	0.57
	NAFSM	0.97	0.95	0.92	0.89	0.85	0.81	0.76	0.70	0.58
	AT2FF	0.98	0.96	0.93	0.90	0.85	0.78	0.70	0.60	0.48
	BPDF	0.98	0.95	0.91	0.87	0.82	0.75	0.65	0.48	0.24
	TSVD	0.98	0.96	0.93	0.90	0.85	0.78	0.69	0.55	0.39
	TMF	0.98	0.96	0.94	0.90	0.86	0.81	0.74	0.64	0.49
	ATF	0.98	0.97	0.94	0.92	0.89	0.86	0.82	0.76	0.66
	SVD-ATMMF	0.89	0.96	0.96	0.97	0.96	0.95	0.94	0.92	0.91

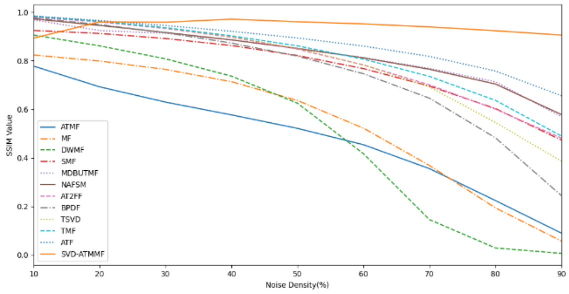


Fig. 12. Graph of SSIM Average Value Of The Sample Images

Journal of Information System and Technology Management
JISTM
EISSN: 0128-1666
Volume 10 Issue 38 (March 2025) PP. 23-39
DOI: 10.35631/JISTM.1038003

A visual comparison study was performed on the filtering results of the proposed method used in Figure 10. The recovery quality of the restored images deteriorates as the noise level rises. The restored images clearly show that the proposed method is capable of removing salt and pepper noise but still contains some white and black dots even in high density noise. When a filter is applied to an image, it removes not only noise, but also some useful information. However, the proposed filter can preserve detail, texture and edge in the image only at low density. Then, the picture quality decreases as the density value increases due to MF. MF provides a weak filtering result for high noise density by removing important information from the image such as unsharp edge and blur of the image. In general, both numerically and visually, the results obtained with the proposed filter are superior.

This is a grayscale image performance metric that is mathematically defined but does not include a model of the human visual system. To compare the original image with the restored image, this measure takes into account the three primary features of the images: contrast, brightness, and structure.

In the PSNR and SSIM evaluation, the proposed filtering technique has slightly lower average PSNR values and SSIM values than other previous methods such as AT2FF, BPDF, TSVD, TMF and ATF from 10% to 20% of noise density. This occurs because the noise detection mechanism with SVD cannot be done if the value of $S_{22,}$ is out of range. The proposed method is superior to the original ATMF method and MF method. However, this does not rule out the possibility that the proposed filtering technique will fail at that noise density for each sample image.

The proposed filtering technique outperformed the other methods. When compared to the other filters, it is observed that the proposed filter has superior metric values. According to Table 3 and Table 4, it can be seen clearly that SVD-ATMF works well in filtering by giving a large average value of PSNR and SSIM, indicating higher performance of a filter compared to other filtering methods from 30% to 90% of noise density. Further, this is supported by the average value of PSNR and SSIM starting at 30% noise density: 21.47 dB/0.6295 (ATMF), 26.06 dB/0.7641 (MF), 28.45 dB/0.8076 (DWMF), 29.55 dB/0.8913 (SMF), 29.89 dB/0.9129 (MDBUTMF), 29.93 dB/0.9161 (NAFSM), 30.99 dB/0.9327 (AT2FF), 29.76 dB/0.9149 (BPDF), 31.41 dB/0.9347 (TSVD), 31.60 dB/0.9357 (TMF), 32.48 dB/0.9447 (ATF), 32.73 dB/0.9582 (SVD-ATMMF).

The average PSNR value between the proposed method and previous methods is given in the graph for comparative quality analysis, as shown in Figure 11 respectively. The proposed filter is positioned at the top of the other filters displaying the best results for the highest noise densities. Meanwhile, the average PSNR value of the proposed method increased for noise density by more than 20%. This is due to the fact that, while the ATM filter may work well in low noise density, it does not function well in high noise density.

Figure 12 illustrates the graph of the SSIM average value between the proposed method and the previous method. The SSIM average value of the proposed method is also higher than that of other methods, which approach value one (1) for noise density of more than 20%. As previously mentioned, a higher value of SSIM implies that more original data is being restored, which is correlated to human perception. Furthermore, experimental results show that the average value of MSE is 40.71, PSNR is 32.38 dB and SSIM is 0.9401 for the sample images.

Journal of Information System and Technology Management
JISTM
EISSN: 0128-1666
Volume 10 Issue 38 (March 2025) PP. 23-39
DOI: 10.35631/JISTM.1038003

Compared to other methods in this experiment, the proposed method offers the best PSNR and SSIM values. This indicates that the proposed method is the most capable of restoring noisy images.

Conclusions

This section presents the conclusion based on the findings in the result and is followed by suggestions for future work. This effort is being made to address the issue of image salt and pepper noise. As stated before, the proposed filtering approach comprises three parts: adding noise to the original image, followed by noise detection. Then, pixel values that have been identified as noisy are restored. The first objective of this study was accomplished, which was to detect the existence of noisy pixels by using the SVD approach. The entry of the diagonal matrix, S_{22} will be used as an indicator to assess the existence of noise on any 3 x 3 template.

The second objective of this study was achieved, which was to remove mixed salt and pepper noise using a combination of both SVD as a noise detector and pixel restoration using ATMF and MF. ATMF is a non-linear windowed filter in the spatial filtering domain. ATMF orders the elements within a filtering window and deletes elements at the beginning of the ordered set with the lowest intensity (grey) level and at the end with the greatest intensity (grey) level. Meanwhile, in the MF, the median value of the ordered pixel value is obtained as the new pixel value. This filtering technique is included in the non-linear filtering group, where filtering results depend on the sequence of pixel values. Then, the performance of the proposed filtering method is evaluated qualitatively (human eye) and quantitatively (MSE, PSNR and SSIM). From the experimental results, the PSNR value and SSIM value of the proposed method achieve the best results when compared to previous methodologies, from 30% to 90% of noise density. Besides, the value of PSNR increases proportionally with the parameter α value, which gives a higher quality of image filtering. Moreover, the SSIM value of the proposed method is higher than other methods. Therefore, this has shown that the proposed filtering method is the efficient way to restore the corrupted image, either raw or benchmark.

The application of this ATM filter for the case of noise removal is not optimal for the resulting image with low quality relatively. The window kernel image is limited to a 3x3 template size. Therefore, the size of the image template may be enlarged to 5x5, 7x7 and many more. In addition, the selection value of the pruning parameter, i.e. α, was performed manually in the algorithm. This had taken a long time to process the filtering method. To overcome the weakness of processing time for the ATM filter, the adaptive concept can be employed by automatically selecting the value of α. This filter was created to remove salt and pepper noise. There are not a lot of noise-based filtering techniques out there currently. This filter designed to remove this noise may also perform well in eliminating other noise types, such as speckle noise, additive noise, and multiplicative noise. Most people are dealing with the images these days are in colour. Thus, changing the method to remove salt and pepper noise in colour images is a good idea. Follow the same principles as grayscale images in the filtering process. However, there are several layers and distinct colour modes in colour images. Several changes to the proposed filtering method are required to eliminate salt and pepper noise in colour image.

Acknowledgement

This research was not funded by any grant.

Journal of Information System and Technology Management
JISTM
EISSN: 0128-1666
Volume 10 Issue 38 (March 2025) PP. 23-39
DOI: 10.35631/JISTM.1038003

References

A. Abdurrazzaq, I. Mohd, A. K. Junoh, and Z. Yahya, “A hybrid of tropical-singular value decomposition method for salt and pepper noise removal,” Turkish J. Electr. Eng. Comput. Sci., vol. 27, no. 3, 2019. https://doi/org/10.3906/elk-1807-93.

A. C. Bovik, T. S. Huang, and D. C. Munson, “A Generalization of Median Filtering Using Linear Combinations of Order Statistics,” IEEE Trans. Acoust., vol. 31, no. 6, 1983. https://doi/org/10.1109/TASSP.1983.1164247.

A. K. Boyat and B. K. Joshi, “A Review Paper : Noise Models in Digital Image Processing,” Signal Image Process. An Int. J., vol. 6, no. 2, 2015. https://doi/org/10.5121/sipij.2015.6206.

A. M. Abdalla, M. S. Osman, H. Alshawabkah, O. Rumman, and M. Mherat, “A Review of Nonlinear Image-Denoising Techniques,” 2019. https://doi/org/10.1109/WorldS4.2018.8611606.

A. Taguchi, “Adaptive spl alpha-trimmed mean filters with excellent detail-preserving,” in ICASSP, IEEE International Conference on Acoustics, Speech and Signal Processing - Proceedings, 1994, vol. 5 https://doi/org/10.1109/TIP.2003.821115.

B. Fu, X. Zhao, C. Song, X. Li, and X. Wang, “A salt and pepper noise image denoising method based on the generative classification,” Multimed. Tools Appl., vol. 78, no. 9, 2019. https://doi/org/10.1007/s11042-018-6732-8.

B. K. Gunturk and X. Li, Image Restoration: Fundamentals and Advances. 2012.

C. T. Lu and T. C. Chou, “Denoising of salt-and-pepper noise corrupted image using modified directional-weighted-median filter,” Pattern Recognit. Lett., vol. 33, no. 10, 2012. https://doi/org/10.1016/j.patrec.2012.03.025.

D. R. K. Brownrigg, “The Weighted Median Filter,” Commun. ACM, vol. 27, no. 8, 1984. https://doi/org/10.1145/358198.358222.

D. S. Zhang, Z. Shi, H. Wang, and D. J. Kouri, “Nonlinear filtering impulse noise removal from corrupted images,” in IEEE International Conference on Image Processing, 2000, vol. 3. https://doi/org/10.1109/icip.2000.899353.

G. Zhu and J. Li, “Some problems of 2D morphological and median filters,” J. Shanghai Univ. (English Ed., vol. 1, no. 3, 1997. https://doi/org/10.1007/s11741-997-0032-2.

G. R. Arce and J. L. Paredes, “Recursive weighted median filters admitting negative weights and their optimization,” IEEE Trans. Signal Process., vol. 48, no. 3, 2000. https://doi/org/10.1109/78.824671.

H. Hwang and R. A. Haddad, “Adaptive Median Filters: New Algorithms and Results,” IEEE Trans. Image Process., vol. 4, no. 4, 1995. https://doi/org/10.1109/83.370679.

H. L. Eng and K. K. Ma, “Noise adaptive soft-switching median filter,” IEEE Trans. Image Process., vol. 10, no. 2, 2001. https://doi/org/10.1109/83.902289.

H. Yanai, K. Takeuchi, and Y. Takane, Projection Matrices, Generalized Inverse Matrices, and Singular Value Decomposition. 2011. https://doi.org/10.1007/s11336-012-9261-9.

K. Aiswarya, V. Jayaraj, and D. Ebenezer, “A new and efficient algorithm for the removal of high density salt and pepper noise in images and videos,” in ICCMS 2010 - 2010 International Conference on Computer Modeling and Simulation, 2010, vol. 4. https://doi/org/10.1109/ICCMS.2010.310.

K. Adedotun, O. Adegoke, and O. Michael, “Noise Reduction Using Arithmetic Mean Filtering (A Comparison Study of Application to Different Noise Types),” Int. J. Sci. Res., vol. 6, no. 2, 2015. https://doi/org/10.21275/ART2017774.

Volume 10 Issue 38 (March 2025) PP. 23-39
DOI: 10.35631/JISTM.1038003
K. S. Srinivasan and D. Ebenezer, "A new fast and efficient decision-based algorithm for removal of high-density impulse noises," IEEE Signal Process. Lett., vol. 14, no. 3, 2007. https://doi/org/10.1109/LSP.2006.884018.

L. Liu, C. L. P. Chen, Y. Zhou, and X. You, "A new weighted mean filter with a two-phase detector for removing impulse noise," Inf. Sci. (Ny)., vol. 315, 2015. https://doi/org/10.1016/j.ins.2015.03.067.

M. González-Hidalgo, S. Massanet, A. Mir, and D. Ruiz-Aguilera, "Impulsive noise removal with an adaptive weighted arithmetic mean operator for any noise density," Appl. Sci., vol. 11, no. 2, 2021. https://doi/org/10.3390/app11020560.

M. Mafi, H. Martin, M. Cabrerizo, J. Andrian, A. Barreto, and M. Adjouadi, "A comprehensive survey on impulse and Gaussian denoising filters for digital images," Signal Processing, vol. 157. 2019. https://doi/org/10.1016/j.sigpro.2018.12.006.

M. Maru and M. C., "Image Restoration Techniques: A Survey," Int. J. Comput. Appl., vol. 160, no. 6, 2017. https://doi/org/10.5120/ijca2017913060

N. N. Win, K. K. K. Kyaw, T. Z. Win, and P. P. Aung, "Image Noise Reduction Using Linear and Nonlinear Filtering Techniques," Int. J. Sci. Res. Publ., vol. 9, no. 8, 2019. https://doi/org/10.29322/ijsrp.9.08.2019.p92113.

N. Iqbal, K. Ahmad, and W. Shahjehan, "High density impulse noise reduction by denoising neighbor pixels," in Proceedings - 2017 13th International Conference on Emerging Technologies, ICET2017, 2018, vol. 2018-January. https://doi/org/10.1109/ICET.2017.8281722.

P. Patel, B. Jena, B. Sahoo, P. Patel, and B. Majhi, "Study of noise removal techniques for digital images," in Biometrics: Concepts, Methodologies, Tools, and Applications, 2016. https://doi/org/10.4018/978-1-5225-0983-7.ch044.

P. K. Sa, R. Dash, and B. Majhi, "Second order difference based detection and directional weighted median filter for removal of random valued impulsive noise," 2009. https://doi/org/10.1109/ICIINFS.2009.5429836.

P. Shrivastava, U. Pratap Singh, and V. Richhariya, "Removal of Impulse Noise using First Order Neighborhood Mean Filter," Int. J. Comput. Appl., vol. 87, no. 4, 2014. https://doi/org/10.5120/15199-3585.

R. H. Chan, C. W. Ho, and M. Nikolova, "Salt-and-pepper noise removal by median-type noise detectors and detail-preserving regularization," IEEE Trans. Image Process., vol. 14, no. 10, 2005. https://doi/org/10.1109/TIP.2005.852196.

R. Öten and R. J. P. De Figueiredo, "Adaptive alpha-trimmed mean filters under deviations from assumed noise model," IEEE Trans. Image Process., vol. 13, no. 5, 2004. https://doi/org/10.1109/TIP.2003.821115.

S. Arora, M. Hanmandlu, and G. Gupta, "Filtering impulse noise in medical images using information sets," Pattern Recognit. Lett., vol. 139, 2020. https://doi/org/10.1016/j.patrec.2018.06.002.

S. Esakkirajan, T. Veerakumar, A. N. Subramanyam, and C. H. PremChand, "Removal of High Density Salt and Pepper Noise Through Modified Decision Based Unsymmetric Trimmed Median Filter," IEEE Signal Process. Lett., vol. 18, no. 5, 2011. https://doi/org/10.1109/lsp.2011.2122333.

S. Kaur, "Noise Types and Various Removal Techniques," International J. Adv. Res. Electron. cs Commun. Eng., vol. 4, no. 2, pp. 226–230, 2015.

S. Zhang and M. A. Karim, "A new impulse detector for switching median filters," IEEE Signal Process. Lett., vol. 9, no. 11, 2002. https://doi/org/10.1109/LSP.2002.805310.

Journal of Information System and Technology Management
JISTM
EISSN: 0128-1666
Volume 10 Issue 38 (March 2025) PP. 23-39
DOI: 10.35631/JISTM.1038003
T. Chen, “Space variant median filters for the restoration of impulse noise corrupted images,” IEEE Trans. Circuits Syst. II Analog Digit. Signal Process., vol. 48, no. 8, 2001. https://doi/org/10.1109/82.959870.

W. Cao, L. Zheng, and K. Dong, “Image adaptive filtering based on the improved Alpha-trimmed mean algorithm,” vol. 18, no. 9, pp. 236–239, 2014.

Y. Dong and S. Xu, “A new directional weighted median filter for removal of random-valued impulse noise,” IEEE Signal Process. Lett., vol. 14, no. 3, 2007. https://doi/org/10.1109/LSP.2006.884014.

Y. Hashimoto, Y. Kajikawa, and Y. Nomura, “Directional difference-based switching median filters,” Electron. Commun. Japan, Part III Fundam. Electron. Sci. (English Transl. Denshi Tsushin Gakkai Ronbunshi), vol. 85, no. 3, 2002. https://doi/org/10.1002/ecjc.1076.

Z. Li, G. Liu, Y. Xu, and Y. Cheng, “Modified directional weighted filter for removal of salt & pepper noise,” Pattern Recognit. Lett., vol. 40, no. 1, 2014. https://doi/org/10.1016/j.patrec.2013.12.022.

Z. Wang and D. Zhang, “Progressive switching median filter for the removal of impulse noise from highly corrupted images,” IEEE Trans. Circuits Syst. II Analog Digit. Signal Process., vol. 46, no. 1, 1999. https://doi/org/10.1109/82.749102.