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Comparison of algorithms for the removal of impulsive noise from an image

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ABSTRACT

Image pre-processing is an important operation that is used to redefine an image to improve human visual perception and information extraction. To de-noise an image tainted with impulsive noise, several state-of-the-art methods have been presented. This work examines and compares several de-noising methods based on the median filter and its advanced non-linear techniques. The research also focuses on the recommended implementation methodologies for using deep learning to de-noise impulsive noise. The paper focuses on one approach's limitations and possible remedies, as well as other techniques that have been offered. The study also identifies several other difficulties that have yet to be resolved.

1. Introduction

Noise is unwelcome data that degrades an image's image quality. The inconsistent variation of contrasts in an image is caused by noise. For future layers of processing, today's era of great accuracy and perfection necessitates a very clear image. It is an important area of research to restore and improve the image quality of a tainted image. The bulk of researchers in this field are interested in de-noising images for better visual perception and information extraction. Image processing for meaningful information abstraction is becoming the backbone of numerous fields, including defence and security, medical diagnostics, astronomical engineering, agriculture, and many more. As a result, a high-resolution, noise-free image is always preferred. However, noise is a component that regularly appears in images. As a result, de-noising an image to obtain a high-quality image is both necessary and difficult in this sector. Several techniques for de-noising an image have been contributed by several researchers, but there is still room for improvement. An image can be contaminated for a variety of reasons, and the type of noise that is added to it deteriorates the image further depending on the noise's characteristics. Gaussian, impulsive, or speckle noise are all possibilities. A comparison of numerous de-noising methods for the removal of impulsive noise from an image is presented in this research.

Basically, linear and non-linear-based methods have been developed for picture restoration from a corrupted image. The linear model [1] has a lower time complexity and works well with increased noise. They stop working when there is a lot of noise in the image, which causes blur and discontinuities. A non-linear model [2] was designed to solve such challenges.

As a result, non-linear filters became the focus of research [3]. When compared to linear filters, they are superior at handling edges and smoothing images. The greatest example is the median filter [1], which was first proposed by Tukey [4]. The Median Filter, which outperforms Linear Filters, has been designed. The median filter performs wonderfully in low-density noise, but as the noise density (ND) increases, it stops working. Researchers created various median filter versions to boost performance. Few work well, and even fewer have downsides when it comes to retaining visual details. Some of the Median Filter-based algorithms that have been created include Filters with a Weighted Median [5], (Switching Median Filter) (SWMF) [7] Adaptive Median Filter (AMF) [8,9,11–17], Adaptive Switching Median Filter (ASMF) [18], Adaptive Switching Median Filter (ASMF) [6,19–25], Adaptive Switching Weighted Median Filter (ASWMF) [26], Adaptive Switching Weighted Median Filter (ASWMF) Adaptive Weighted Mean Filter [27–31], Alpha Trimmed Mean and Median Filters [32,33], and so on. Diffusion-based techniques [34], total variation-based approaches [35], and other image denoising algorithms have been developed in recent decades. Wavelet/curvelet-based approaches [28,29,37–41], and probabilistic based method [42–46,49–53].

A comparative analysis of various de-noising algorithms for impulsive noise removal is offered in this paper. To date, certain comparative contributions relating to the evaluation of filtering algorithms have been documented [54–58]. This study presents a comparative examination of

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many filters and their various versions in terms of functionality and relative performance. Grey-scale images are employed to test the algorithms' adaptability because their application is desired in a variety of sectors for varied objectives, such as clinical diagnosis, forensics, radar, and sonar systems. In comparison to the previously published techniques, each algorithm identifies and removes noise in a different or more advanced manner. The state-of-the-art algorithms stated above will be reviewed and contrasted in the next section. Under performance evaluation, the performance comparison is done both visually and objectively. Some mathematical formulas are used in the objective analysis, which can be a useful tool for estimating image quality. PSNR, MSE, Mean Absolute Error (MAE), and Structural Similarity Index are the objective measures used to analyze performance indicators (SSIM).

2. Working principle-based analysis of the state-of-art

For a successful image processing activity, images with superior visual acuity are always needed. When it comes to achieving the desired image quality, de-noising is crucial. One of the most essential approaches for image de-noising is filtering. Following is a detailed examination of some developed algorithms:

2.1. Standard median filter (SMF)

The Standard Median Filter (SMF) [1] is a simple basic position determination filter that was developed as a non-linear filter. It operates by processing the centre element of the window in question to reduce impulsive noise. The processing pixel may have a value of "0″ (black), "255″ (white), or any other value between 0 and 255, after which the pixel is replaced by finding the window's median. The major flaw in this approach is that all pixels are treated the same way, whether they are affected or not. Edge preservation is also a problem for SMF. Consider the 3 × 3 window in Fig. 1 to better understand the functioning principle.

For calculations, the centre element is taken into account. As a result, the median for 255 in the centre is derived by ascending the values in the window, i.e. (0, 110,120, 180, 180, 255, 255, 255, 255). The median value will be used to replace the original centre pixel 255, which is now the centre element of the formatted values, i.e. 180. Every pixel element is treated in the same way.

2.2. Switching median filter (SWMF)

SWMF [8] is a significant advancement in the detection of noisy pixels with high accuracy. It first detects the faulty pixel before using median filtering. The SWMF is a two-step process. Initially, a test determines whether a particular pixel is impulsive or not: a pixel is corrupted if the threshold value is less than the absolute difference determined between the median of the considered window and the processed pixel's intensity [72]. If a contaminated pixel is discovered after testing, a classic median fitter is used for restoration; if the considered pixel is not found to be contaminated, it is not modified. The main disadvantage of the SWMF method is that it substitutes a noisy pixel with a nearby median value without taking into account local features such as edges. As a result, some picture and edge information are not retrieved adequately.

120	180	0
255	255	180
110	255	255

Fig. 1. Considered 3 × 3 window.

2.3. Switching median filter with boundary discriminative noise detection (BDND)

This variant of the Median method [8] adapts to extremely polluted photos and mitigates difficulties caused by pixel misjudgement. With the use of a binary decision map, it is designed to identify degraded pixels. The binary decision map categorizes all pixels into one of three groups. Uncorrupted, low-intensity and high-intensity corrupted pixels are the three classes. The window size is determined by the noise density, ensuring that at least one-third of the pixels are uncorrupted. Only the degraded pixels are processed by BDND, which reduces the time complexity. To separate the pixels into three classes, two well-defined specified limits are required. The precision of classes is, without a doubt, dependant on the accuracy of recognized boundaries. Increased window size is required to accommodate one-third of uncorrupted pixels in the processing window, which causes additional blurring. This approach calculates the median value using non-corrupted pixel elements, un-sharpening the edges in the resulting image [9].

2.4. Adaptive median filter (AMF)

To date, other variations and better approaches based on SMF have been documented, such as AMF [10–16], where the size of the considered window is adjustable. The AMF is used to increase the filter's adaptability, allowing it to modify its size as needed based on the estimation of local noise density. It is effective at removing mixed impulses with a high likelihood of occurrence while maintaining clarity. Because the median filtering is only applied to the contaminated pixels, this method is faster to implement. The window size of an adaptive median filter is adaptively extended based on the statistics of the min, median, and max values in the current analysis window. It normally starts with a window of size 3 and grows to the maximum permitted size until the median value is in the middle of the two extremes. AMF is frequently utilized by researchers to construct advanced algorithms due to its ease of implementation and high noise removal capacity.

2.5. Adaptive switching median filter (ASWM)

Unlike the switching median filter, the ASWM [18] does not require an a priori threshold. The threshold is computed locally from the pixel intensity in a sliding window in this manner. In the current window, the weighted mean value and weighted standard deviation are determined. The weights are the inverse of the distance between the considered pixel and the pixel elements' weighted mean value. As a result, impulsive noise does not taint the determination of these data, which are used to calculate the Threshold. The weighted mean is assessed iteratively in each window. The weighted standard deviation is also calculated, as well as the Threshold.

2.6. Adaptive dynamically weighted median filter (ADWMF)

The weighted median filter [5] is combined with a basic impulse detector approach in ADWMF [29]. The approach adjusts the window size based on the noise density. The weighted median filter is updated once impulse noise is detected by dynamically giving zero weight to the noisy element in the appropriate frame.

2.7. Noise adaptive fuzzy switching median filter (NAFSM)

The detection and filtering phases of NAFSM [22] reduce impulsive noise. To find the corrupted pixel, the method uses the histogram of the noisy image. The resultant noisy pixel is then sent to the filtering stage, which processes the corrupted pixel while leaving the noise-free pixel elements alone. To find the affected pixel, it looks for local maxima at either end of the histogram. To identify the noisy pixel, a binary noisy masque is constructed. The noisy pixel is given a value of 0 while the others are given a value of 1. The estimated correction term is used to replace the noisy pixel in the filtering stage, based on the mask's marking for noisy pixels.

2.8. Trimmed filter

To reduce the temporal complexity and retain the edges, researchers turned to the trimming strategy, which was combined with state-of-the-art algorithms. The trimmed mean and its extension, the trimmed median filter (TMF) [33,36,59,60] are two of the more intuitively pleasant estimators of this sort.

The trimmed mean is claimed because, rather than averaging the entire informational set, a few data points are removed (trimmed) and the remaining data points are averaged. The most extreme data values, both low and high, are deleted, with an equal amount of points reduced at each end (symmetrically trimmed). After eliminating the data, the alpha-trimmed mean [32] is calculated by simply arranging it from low to high and averaging the centre values of the organized cluster. The trimming parameter alpha, whose value is somewhere between 0 and 0.5, controls the number of data points that are dropped from the normal.

2.9. Un-symmetric trimmed median filter (UTMF)

In UTMF [44], the pixel elements of the considered window are sorted after removing pixels with intensities 0 and 255. This operation is used to calculate the noise-free pixels' median value. The estimated median value is then utilized to replace the processing pixel in question. The algorithm takes advantage of the asymmetric aspect of the pixel-dropping technique, because in a symmetric way of dropping the pixel, the image's information content is lost, resulting in information loss. This method is used in several typical state-of-the-art algorithms, which will be examined in more detail later.

2.10. Modified decision-based un-symmetric trimmed median filter (MDBUTMF)

MDBUTMF [44] was created to solve the problem of all pixels in the examined window being either 0 or 255. The technique begins by finding the noisy candidate in an image tainted with impulsive noise. The associated pixel element is left unmodified if the intensity levels are between the two extreme grey values. MDBUTMF processes pixels with a value between the two extremes.

2.11. A new method based on pixel density in salt and pepper noise removal (BPDF)

The most repeating noise-free pixel is used to get the median value in this method [46]. To develop the algorithm, a range between the two extremes is chosen. If a processing pixel is identified to be noisy, the algorithm looks for at least one pixel within that range and at least one pixel beyond that range. Outside the range, the pixel is assumed to be noise-free. If this is the case, the most repeating pixel intensity is searched once more. The processing pixel is replaced with the median of the repeated pixel. Because the range chosen is superficial, the algorithm built fails to keep the image's details.

2.12. Probabilistic decision based filter (PDBF)

Trimmed Median Filter (TMF) and Patch Else Trimmed Median Filter (PETMF) are fused independently for low and high ND to de-noise a picture contaminated with impulsive noise in the PDBF [47]. When the ND is less than 50%, TMF is used, but PEITMF is used when the ND is larger than 50%. When compared to the great majority of other state-of-the-art, the PDBF performs wonderfully, but it lacks a powerful arrangement when the NFP is even included when computing the trimmed median. As a result, the majority of pixels in a de-noised image are unable to estimate the data connected to the original image correctly, resulting in image degradation after de-noising.

2.13. Adaptive probability filter (APF)

The author used a probabilistic technique to construct a novel detection module in the APF [48]. To distinguish the impulsive noise, two extreme grey levels of the image are used, coupled with the spread of noise. For noise detection, the evaluated processed pixel is compared to the adjacent pixel to determine its suitability as an image element. A noise pixel is highlighted if it is detected during the detection step. The processing pixel is the one that has been marked. To replace the processing pixel, the number of noise-free pixel elements is calculated and compared to the estimated threshold value to replace the pixel in question. If there are no noise-free elements detected, the mean filter is employed to replace them. APF also does an excellent job of judging and retaining noise-free pixels. If it does not perform its role as an image applicant, it develops a good relationship in replacing polluted pixels. The algorithm's performance degrades as the noise density rises. When the noise density in an image exceeds 70%, it loses its ability to maintain the image's characteristics and fine details. This failure occurs because it employs a mean filtering strategy in the absence of noise-free pixels in the affected window.

3. Performance evaluation based on simulation results

Under filters based on the median, adaptive median, and advanced non-linear filter, several simulations are done using the state-of-the-art methods outlined above. The datasets were obtained from reputable websites such as imageprocessingplace.com and sipi.usc.edu. The BSDS300 dataset and images of Lena, Lady, House, Pepper, Mandrill are used. The photographs have been reduced to 160 by 120 pixels so that they can be used in all of the state-of-the-art. The median filter techniques, as well as an enhanced version of it, are implemented in the MATLAB R2013b environment. The suggested method's performance is assessed using quantitative measures such as mean square error (MSE), peak signal-to-noise error (PSNR), mean absolute error (MAE), and structural similarity index measure (SSIM) that are formulated as follows:

$$MSE = \frac{\sum_{i,j}^{m,n}\left(Z_{i,j} - Z_{d_{i,j}}\right)^2}{m \times n} \tag{3}$$

$$PSNR = 10\log_{10}\left(\frac{255^2}{MSE}\right) \tag{4}$$

$$MAE = \frac{\sum_{i,j}^{m,n}\left|Z_{i,j} - Z_{d_{i,j}}\right|}{m \times n} \tag{5}$$

where 'Z' denotes the clean image and 'Z_d' denotes de-noised image. The size of the image is m × n.

$$SSIM(X,Y) = \frac{i(2\mu_X\mu_Y + C1) + (2\sigma_{XY} + C2)}{i(\mu_X^2 + \mu_Y^2 + c1) + (\sigma_X^2 + \sigma_Y^2 + C2)} \tag{6}$$

$$c1 = (K_1L)^2 \tag{7}$$

$$c2 = (K_2L)^2 \tag{8}$$

where, 'μ_X', 'μ_Y' denote the average and 'σ_X', 'σ_Y' represent the variance of image 'X' and 'Y', respectively; 'σ_{XY}' represents the co-variance. 'K_1' and 'K_2' are the constant. The value of 'L' in an 8-bit grayscale picture is 255. The standard pictures, BSDS300 dataset, and BBBC041 dataset are used to simulate algorithms based on median filters and their enhanced version, and the results are summarized. Tables 1 and 2 contain all of the obtained results. Figs. 3–5 shows the corresponding graphical

Table 1
Performance comparison of all considered state-of-the-art algorithms in terms of PSNR using image Lena in various noise densities.

Algorithms	Noise Density				
	10%	30%	50%	70%	90%
APF	**43.55**	**40.77**	**36.14**	**32.64**	**25.53**
BPDF	41.17	38.34	34.17	27.63	22.78
PDBF	42.87	39.89	35.72	31.11	24.15
MDBUTMF	40.76	34.82	32.98	26.46	21.18
DBA	40.11	34.17	31.68	25.45	20.71
UTMF	36.18	31.85	29.77	24.88	19.48
TMF	28.63	25.85	21.44	17.17	15.66
NAFSM	39.36	34.52	31.88	25.66	20.11
ADWMF	38.68	34.44	28.68	24.46	21.33
ASWM	37.11	33.75	24.45	20.14	18.66
AMF	36.77	33.25	22.11	17.52	16.88
SWMF-BDND	34.22	32.35	27.84	23.54	20.23
SWMF	29.57	25.82	24.21	17.11	8.12
SMF	27.63	24.11	23.47	16.16	7.78

Table 2
Performance comparison of all considered state-of-the-art algorithm in terms of SSIM using image 13,026 from BSDS300 Dataset.

Algorithms	Noise Density				
	10%	30%	50%	70%	90%
APF	**0.9526**	**0.9266**	**0.8496**	**0.8145**	**0.7841**
BPDF	0.8687	0.8487	0.8092	0.7787	0.6901
PDBF	0.8714	0.8622	0.8133	0.7814	0.6918
MDBUTMF	0.9014	0.8615	0.8291	0.7912	0.7211
DBA	0.8614	0.8461	0.8072	0.7796	0.7011
UTMF	0.8512	0.8321	0.7921	0.7632	0.6922
TMF	0.8141	0.7955	0.7628	0.6836	0.5814
NAFSM	0.9289	0.8711	0.8116	0.7754	0.6722
ADWMF	0.9255	0.8689	0.7869	0.6933	0.6741
ASWM	0.9235	0.8424	0.7087	0.6478	0.6187
AMF	0.9155	0.8387	0.6926	0.6087	0.5974
SWMF-BDND	0.9089	0.8231	0.7769	0.7034	0.6543
SWMF	0.8098	0.7326	0.7011	0.6339	0.4428
SMF	0.7787	0.7002	0.6813	0.6241	0.4316

representations for a better understanding. The PSNR value continuously increases with the incorporation and development of advanced approaches based on the median filter, as seen in Table 1 and Fig. 2.

Furthermore, algorithms that use noise detection techniques offer additional benefits that can be seen in the findings. In comparison to other state-of-the-art algorithms, a superior algorithm should have a lower MSE, a higher SSIM, and a higher PSNR value. As shown in Tables 1 and 2 and Figs. 2 and 3, the algorithms adopting a probabilistic method have a higher PSNR and SSIM value than the previously proposed algorithms. Because the algorithms built utilizing a probabilistic method have a stronger noise identification strategy, they perform better. They devised a reliable method for determining whether a pixel contains information from the original image or is noise. Trimmed Median Filter (TMF) and Patch Else Trimmed Median Filter (PETMF) are fused independently for low and high ND to de-noise a picture contaminated with impulsive noise in the PDBF [47]. When the ND is less than 50%, TMF is used, but PEITMF is used when the ND is larger than 50%. When compared to the great majority of other state-of-the-art, the PDBF performs wonderfully, but it lacks a powerful arrangement when the NFP is even included when computing the trimmed median. As a result, the majority of pixels in a de-noised image are unable to estimate the data connected to the original image correctly, resulting in image degradation after de-noising. As a result, they replace each pixel with arbitrary values that have no relationship to neighboring or local pixels. Advanced non-linear filters, such as NAFSM, MDBUTMF, BPDF, PDBF, and APF, have a higher de-noising ability. Due to the creation of a good detection technique, APF outperforms the others. These filters can provide some edge break and blurring effects in high noise densities. It can be seen in Figs. 4 and 5. The APF may be further improved by utilizing some improved algorithm of median filter instead of the basic median filter.

The medical images most often get intact with impulse noise due to improper imaging. The APF filter in its present form can be utilized in the medical field for enhancing the image quality for further diagnosis.

4. Conclusion

This work gives an examination based on a comparison of the approach and performance of a state-of-the-art algorithm for removing impulsive noise from a grayscale image that was developed. Extensive simulations are run, and the results are tabulated as well as a graphical depiction. For visual analysis, the obtained denoised photos are also displayed. The benefits, drawbacks, and solutions to such drawbacks by other established algorithms are discussed. Several variants were created by combining the adaptive filtering approach with the median to alter the window size. This method has gained popularity, however, the main issue of removal in high noise density, edge preservation, and blurring remains.

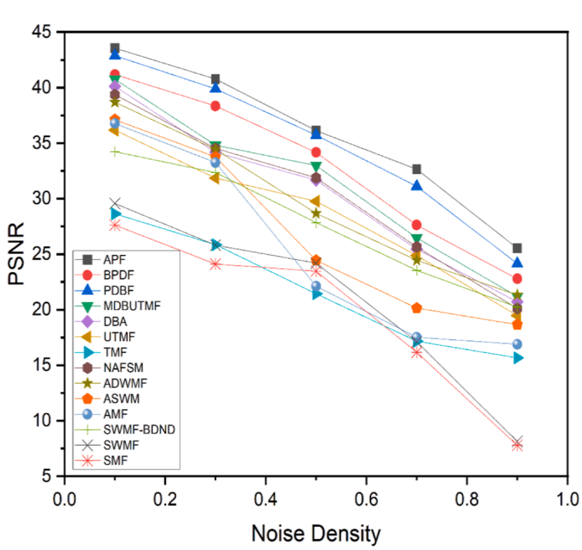

Fig. 2. Graphical comparison of all considered state-of-the-art in terms of PSNR using image Lena.

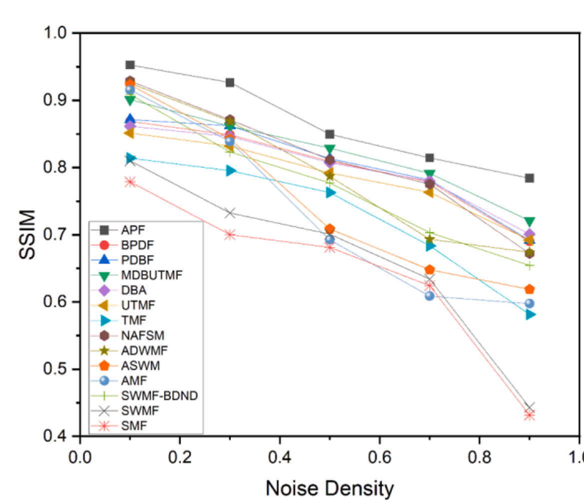

Fig. 3. Graphical comparison of all considered state-of-the-art in terms of SSIM using image 13,026 from BSDS300 Dataset.

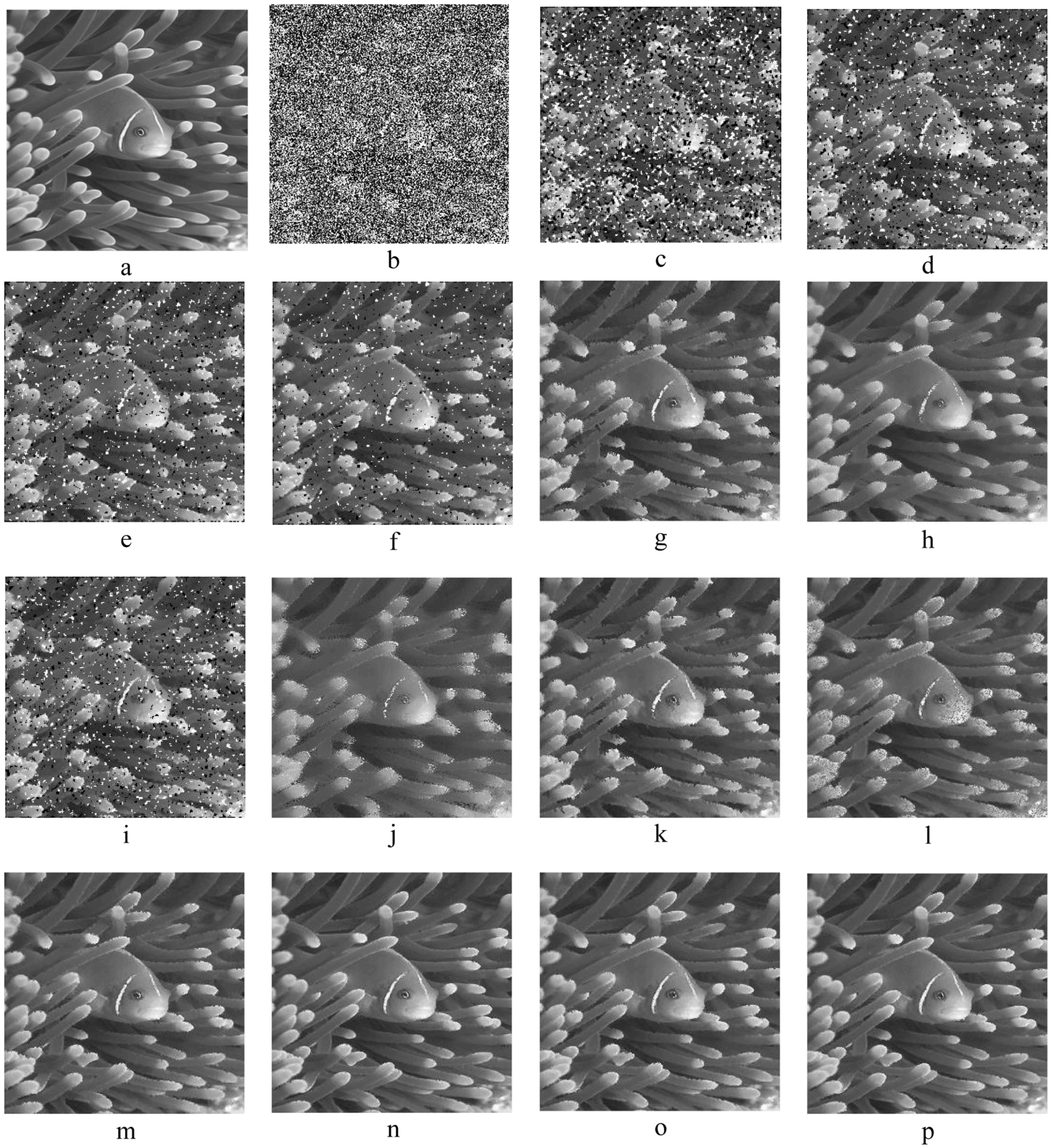

Fig. 4. Visual Comparison of the obtained images using considered algorithms: (a) Original image, (b) Noisy image with 50% ND, (c) SMF, (d) SWMF, (e) SWMF-BDND, (f) AMF, (g) ASWF, (h) ADWMF, (i) TMF, (j) NAFSM, (k) UTMF, (l) DBA, (m) MDBUTMF, (n) PDBF, (o) BPDF, and (p) APF.

Trimmed mean and median were also established, which eliminated the problem of the average being pulled to an arbitrary figure. This development was a significant step toward resolving the blurring problem. Researchers began to utilize a probabilistic technique in conjunction with median variants. Both PDBF and APF perform well in terms of denoising, however, PDBF has trouble with the issue of an even number of noise-free pixels, which causes images to blur at high noise density. Along with good detection, APF uses a mean filter that fails to keep the original information at high noise density. As a result, a robust approach to address the difficulties in PDBF and APF can be devised in the future. Because this filter has some of the constraints stated in the previous sections, it can be enhanced further to create a more robust algorithm.

Ethics approval

This article's work has been tested on the already available data in the research community.

Declaration of Competing Interest

The authors declare that they have no known competing financial

Fig. 5. Visual Comparison of the obtained Lena images using considered algorithms: (a) Original image, (b) Noisy image with 50% ND, (c) SMF, (d) SWMF, (e) SWMF-BDND, (f) AMF, (g) ASWF, (h) ADWMF, (i) TMF, (j) NAFSM, (k) UTMF, (l) DBA, (m) MDBUTMF, (n) PDBF.

interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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