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Noise Density Range Sensitive Mean-Median Filter for Impulse Noise Removal

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Abstract. A new noise density range sensitive algorithm for the restoration of images that are corrupted by impulse noise is proposed. The proposed algorithm replaces the noisy pixel by mean, median or pre-processed values based on noise density of the image. The proposed filter uses a unique approach for recovering images corrupted with very high noise densities (over 85%). It also provides significantly better image quality for different noise densities (10–90%). Simulation results show that the proposed filter outperforms in comparison with the other nonlinear filters. At very high noise densities, the proposed filter provides better visual representation with 6.5% average improvement in peak signal-to-noise ratio value when compared to state-of-the-art filters.

Keywords: Median filters · Salt and pepper noise · Mean filters · Noise density-based filter · Image processing

1 Introduction

Salt and pepper noise, also known as impulse noise, is often introduced during the transmission of an image through a noisy medium. It is caused due to sudden disturbance in the image during transmission and electromagnetic interference in the environment. The pixels attain extreme values of either 0 or 255 in case of a greyscale image [1]. Filters are effective tools for de-noising the image. They could be a piece of hardware or software that performs an algorithm on the input signal to produce de-noised image. Linear and nonlinear filtering [3–9] approaches are one of the most prevalent filtering techniques.

Various approaches such as interpolation-based filters [6] are also presented for de-noising images, but their performance is only good when they get a sufficiently large amount of data. Other techniques like weighted median approach [7, 8] mostly divide information into two or more groups, and based on the weighting factor, it decides which group to pick for processing. Although at high noise density, these filters fail catastrophically due to the lack of original pixels in created groups. Many trimmed

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median filters [4] also exist that provide satisfying solutions only in specific noise density ranges. Several linear and nonlinear filters are proposed which are good at a certain limit of noise density, but after that, they consequently lead to a loss in edge detail and blurring of image [9]. However, it is often ignored that different noise densities need range specific solutions.

To overcome these problems, a new noise density range sensitive mean-median filter (NRSMF) is proposed, which is a combination of both linear and nonlinear filters that provide range-specific solutions for de-noising images.

2 Related Work

Various filters are proposed for detecting and removing the impulse noise [2]. The mean and median filters are proposed at first [3–5]. In mean, a 3×3 window is constructed across the pixel, and mean of all pixels in the window replaces the processed pixel. The main problem with mean filters is their inability to preserve edges because no original pixel values are restored in the process. For this reason, exploration in the field of median filters [4, 5] started where the corrupted pixel is replaced by the median of 3×3 window. Though this filter performs excellently on lower noise densities, for high noise densities, most of the pixels in the 3×3 window are corrupted. So, most of the pixels will remain corrupted after processing, which results in a poor image quality.

Many nonlinear filers are introduced to overcome the problems of mean and median filters, such as decision-based median filter (DBAMF) [6]. In DBAMF, a specific type of sorting is done on the 3×3 window, so that the resultant matrix has the median as its central pixel of the window. The processed pixel is then replaced by the centre pixel. In case the median turns out to be noisy, the pixel being processed is replaced by the nearest non-noisy pixel. The major drawback of this filter is that, under high noise density condition, the median generally turns out to be noisy. This results in repetition of the same pixel, again and again, causing a blurring effect.

To improve the performance of DBAMF, new filters like unsymmetric trimmed mean filter (UTMF) [7] and unsymmetric trimmed midpoint filter (UTMP) are introduced. The UTMF performed better on lower noise densities, whereas UTMP is good at higher noise densities. In UTMF, the mean of non-extreme values in a 3×3 window is taken for every pixel. On the other hand, in UTMP the mid-point of non-extreme values is taken. The main problem with these two algorithms is that even though they work great in their own domain, they fail catastrophically when considered individually.

Another nonlinear filter, modified decision-based un-symmetric trimmed median filter (MDBUTMF) [9] overcame these problems. In which, a fixed 3×3 window is considered across the noisy pixel and median of the uncorrupted values in the window is used to replace the noisy pixel. If the window contains only corrupted pixels, the pixel is replaced by the mean of all the pixels in the selected window. This process also performs well at lower noise densities, but at higher noise densities the noisy pixel is replaced by the mean of the corrupted pixels in the 3×3 matrix. This causes a streaking effect throughout the image. To overcome this issue, fast switching-based median–mean filter (FSBMMF) [10] is introduced. It uses the mean of the previously processed pixels in the 3×3 window when the median turns out to be noisy. This results in lower streaking.

This method uses a unique approach for the corner and last row/column pixels. These pixels are replaced by the previous pixel in their respective row or column. For the corner pixel, the mean of uncorrupted values of the 5 × 5 window is considered. However, the main problem with FSBMMF is that corrupted pixels are taken into consideration in the 3 × 3 window while taking the median, which causes inaccuracies and corruption in the estimated values.

A different approach has also been introduced, which includes the usage of interpolation for replacing the corrupted pixel with the processed pixel; one such example is recursive cubic spline interpolation filter (RSIF) [11]. The only benefit of this technique is that interpolation is a better approximation technique referring mathematically. During higher noise densities, it is not as useful because it does not get ample amount of data to make accurate predictions. Moreover, this algorithm is just like MDBUTMF, where the median is used instead of interpolation. Also, this filter takes a considerable amount of computational time than other existing filters. Thus, a new three-value weighted median (TVWA) [12] with variable size window is proposed. The idea is to divide the non-corrupted values of the processing window into three groups. The first group contains all the non-corrupted pixels closer to the maximum value; the second group contains all the non-corrupted pixels closer to the middle value and the third group with pixels closer to the minimum value. So, based on the weighting factor of the group, the corrupted pixel is replaced by the product of the weighting factor of each group and respective maximum, minimum and middle value. However, if the window in consideration only had corrupted values, the window size is increased until an uncorrupted pixel is encountered. This approach is an improvement over other existing adaptive median filters, which use variable size windows during high noise density that resulted in lower details in the image.

Another method to cure the above-mentioned issues is adaptive switching weighted median filter (ASWMF) [13]. In this method, every pixel should have to pass a certain set of conditions to make the decision whether it is a corrupted pixel or not. So, if the pixel is not 0 or 255 and the mean of the pixel in the 3 × 3 window is not 0 or 255, respectively, then the pixel is noise-free. For the processing, this algorithm uses the concept of repeating the pixel in the variable size window a specific number of times and then taking the median. Also, for median calculation, it is first checked whether the length of the window is even or odd, which further has certain repeating concepts to process them, respectively. The major problem with the filter is that it takes a lot of computational time due to its complexity when compared to other filters. Also, at higher noise densities the pixel is replaced by nearest non-noisy pixel when 3 × 3 and 5 × 5 windows fail to execute, which results in blurring and loss of details in the image.

One of the latest approaches in context with resolving salt and pepper noise is different applied median filter (DAMF) [14]. The method first creates a binary image from the corrupted image by setting the extreme pixels as 1 and others with 0. Further, these values are used to determine whether a pixel is corrupted or not. So, if the pixel is corrupted, then a 3 × 3 window is constructed across it. The window size is increased until one non-noisy pixel is encountered in the inspection window. However, the window size is limited to 7 × 7. Once a non-noisy pixel is encountered in the window, median of all the non-extreme pixels is used to replace the corrupted pixel. Once all the corrupted pixels have been operated upon, the resultant image is again converted into a binary format as before. If a corrupted pixel is encountered, then a 3×3 window is formed around it again, and a median of the uncorrupted pre-processed values replaces the pixel. The benefit of this method is that pre-processed pixels are used to calculate higher noise density conditions. Also, rather than zero padding, the edges are symmetrically padded, thus reducing the probability of creating higher noise density windows on the edges. The major disadvantage of this filter is that under very high noise density 5×5 and 7×7 windows are used for median calculation, which results in loss of image quality.

It can be observed from the above-mentioned techniques that their performance at higher noise density is not up to the mark. The algorithm presented in the next section overcomes the above-mentioned problems.

3 Proposed NRSMF Algorithm

This section first presents the proposed NRSMF algorithm flow chart with its comprehensive explanation of each step. Then, various cases of proposed algorithms are explained with the help of suitable examples.

3.1 Proposed Algorithm Flowchart

The flowchart of proposed NRSMF algorithm is shown in Fig. 1. It de-noises the given image by performing following steps:

Step 1: Calculate approximate noise density (ND) of image.

Step 2: If pixel (P) is either 0 or 255, consider it as noisy pixel ($\mathrm{P_n}$).

Step 3: If ND $\Longleftarrow$ 25%, consider a 3×3 window ($\mathrm{W}_{3\times3}$) across $\mathrm{P_n}$. Evaluate noise-free window ($W^{nf}_{3\times3}$) by eliminating all $0'$s and $255'$s. Calculate median of $W^{nf}_{3\times3}$, if median is non-noisy, go to Step 2 for processing of next pixel, else go to Step 6.

Step 4: If ND > 25%, consider $W^{nf}_{3\times3}$ and calculate mean, if mean is non-noisy, go to Step 2.

Step 5: If mean is noisy, consider $W^{nf}_{5\times5}$. If number of non-noisy pixels left in $W^{nf}_{5\times5}$ is at least 2, take mean of $W^{nf}_{5\times5}$.

Note: Since the above step (Step 5) uses W_5 × 5, it is quite possible that P_n is corner pixel in the window, which has least amount of co-relation with corrupted pixel. This led to a conclusion that it is better to have at least two non-noisy in $\mathrm{W}_{5\times5}$ as to have more information about $\mathrm{P_n}$.

Step 6: Check for corner or boundary pixel.

(a) If P_n is corner pixel, replace P_n by median of $W^{nf}_{5\times5}$
(b) If P_n is boundary pixel, replace P_n by previously processed pixels in their respective row/column.

Step 7: After processing, if P_n is still noisy, do the following:

(a) If ND $\Longleftarrow$ 85%, replace P_n by mean of previously processed pixels in $W_{3\times3}$.

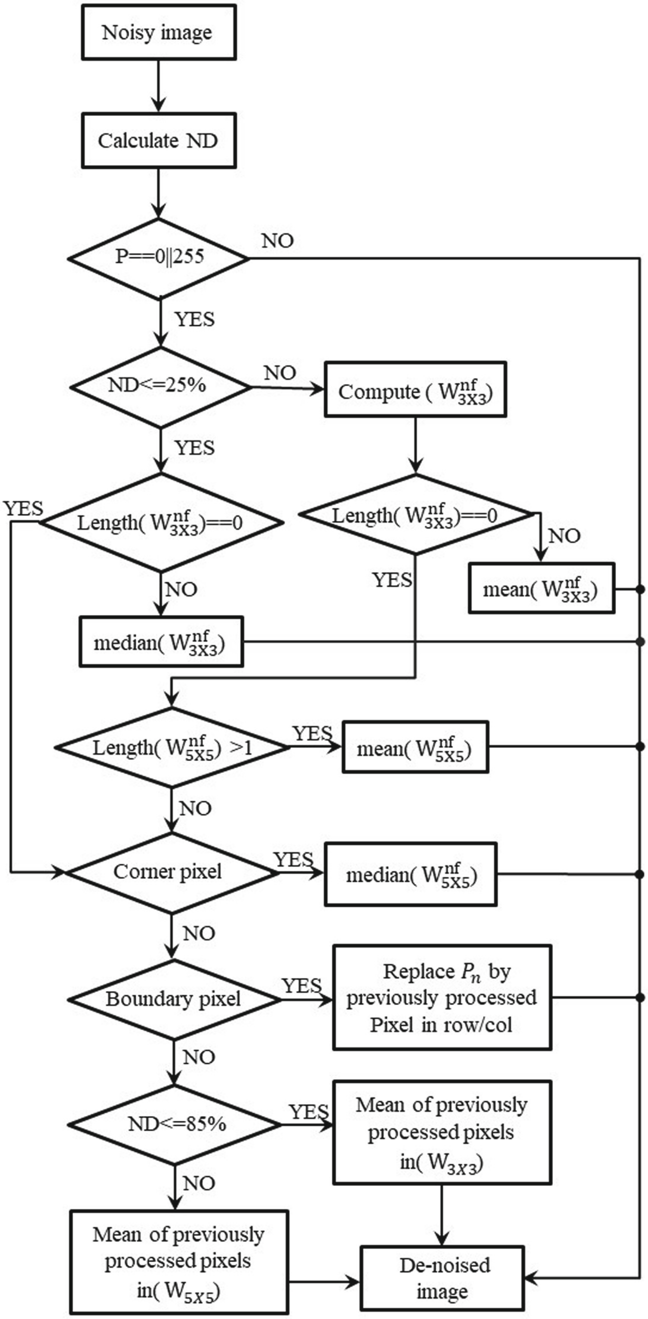

Fig. 1. The proposed algorithm flowchart

***Note**: It is observed that the previously processed pixels are already close to the actual values. Hence, they produce better estimates during mean calculation.

(b) If ND > 85%, replace P_n by mean of the previously processed pixels in $W_{5\times5}$.

Note: For ND greater than 85%, most of the processed pixels have been estimated from few original values. That is why $W_{5\times5}$ is taken instead of $W_{3\times3}$ as it increases the chance of reaching the value of original pixel.

It can be observed that all the noisy pixels are computed by non-extreme pixels which should provide better results. The next subsection explains the above-mentioned algorithm with the help of a few examples.

3.2 Examples Related to Proposed Algorithm

In Figs. 2 and 4, examples of image corrupted with noise density less than 25%, between 25 and 85% and above 85%, respectively, are taken. For Fig. 2, to evaluate corner pixel, first $W_{3\times3}$ is considered, but all the pixels are noisy in the window, so condition for corner pixel is applicable, i.e., a $W_{5\times5}$ is considered, where it finds non-noisy pixels. Then, the corrupted pixel is replaced by median of $W^{nf}_{5\times5}$.

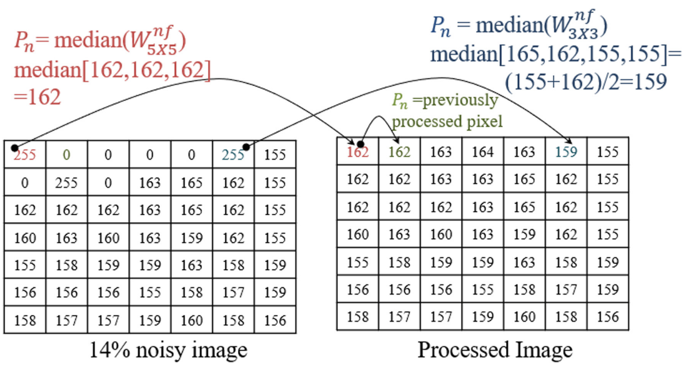

Fig. 2. Noise density is less than 25%

For Fig. 3, the corrupted pixel in 1st row, 5th column is replaced by previously processed pixel, because the number of uncorrupted pixels is less than 2 in $W_{5\times5}$. So, according to algorithm, the unprocessed boundary pixel is replaced by previously processed row/column pixel.

In Fig. 4, the pixel in 5th row 4th column, a $_{3\times3}$ is considered, but all the pixels in $W_{3\times3}$ turn out to be noisy. So, we check for $W_{W5\times5}$. But now, the length of $W^{nf}_{5\times5}$ is less than 2, thus the pixel is replaced by mean of previously processed pixels in $W_{5\times5}$.

4 Simulation Results and Analysis

The performance of the NRSMF and other existing filters namely DBAMF, MDBUTM, FSBMMF, RSIF, TVWA, ASWMF and DAMF are tested on different greyscale images

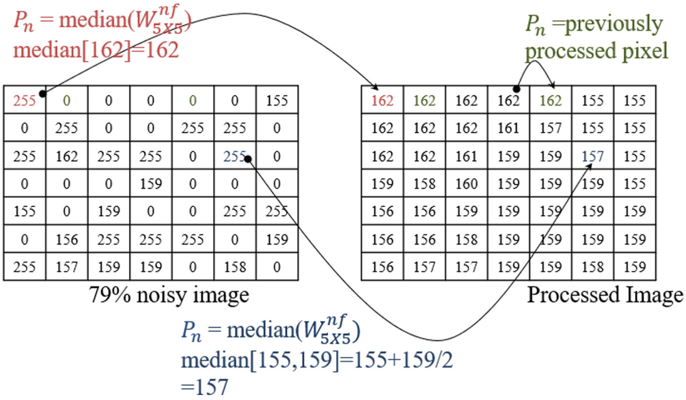

Fig. 3. Noise density is between 25 and 85%

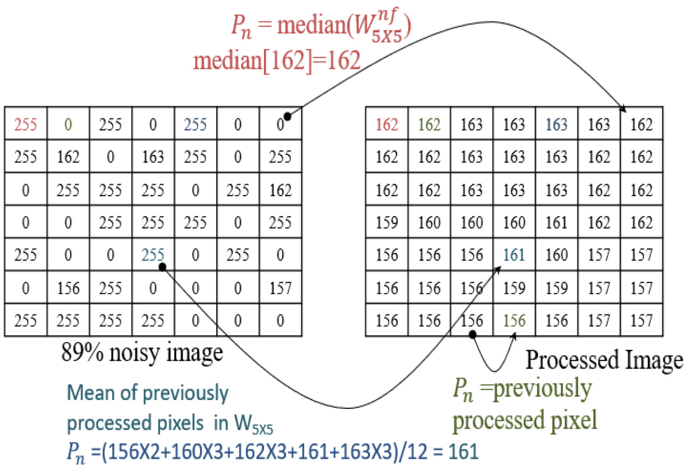

Fig. 4. Noise density is greater than 85%

like Boat (512 × 512), Zelda (512 × 512), Lena (512 × 512) and coloured images, e.g., peppers image (512 × 512). These images are corrupted with impulse noise. The value of peak signal-to-noise ratio (PSNR) and structural similarity index (SSIM) [15] is calculated with varying noise densities. The SSIM is a method for predicting the deduced quality of digital images and PSNR (dB) is the ratio between maximum possible signal power to the power of noise in corrupted image. Mathematically,

$$\text{PSNR} = 10\log_{10}\left(\frac{\text{Max}^2}{\text{MSE}}\right) \tag{1}$$

$$\text{MSE} = \frac{1}{MN}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}\left[x(i,j) - y(i,j)\right]^2 \tag{2}$$

where MSE is mean square error, x and y represent input and output images, respectively. The parameter M and N represent dimensions of the image and Max is maximum pixel value of the image.

$$\mathrm{SSIM}(x,\ y) = \frac{\left(2 \cdot \mu_x \cdot \mu_y + c_1\right)\left(2 \cdot \sigma_{xy} + c_2\right)}{\left(\mu_x^2 + \mu_y^2 + c_1\right)\left(\sigma_x^2 + \sigma_y^2 + c_2\right)} \tag{3}$$

where μ_x, σ_x^2 and μ_y, σ_y^2 are mean and variance of x and y, respectively. σ_{xy} represent covariance of x and y, and c_1, c_2 are constants.

Below subsection provides the analysis of the proposed algorithm on higher noise densities, followed by analysis for wide range of noise densities in context with PSNR, SSIM and visual representation of the image.

4.1 Analysis on Higher Noise Density

In Table 1, the average PSNR and SSIM values are shown for the NRSMF and existing filters, when Boat, Zelda and Lena images each of 512 × 512 are considered. The noise density is varied from 85 to 99%. The simulation results show that at higher noise densities, NRSMF has a superior performance in comparison with other filters even over 95%. Figures 5 and 6 provide the plot for the same. The trend clearly demonstrates that the PSNR and SSIM of NRSMF are better than other existing filters. The simulation results verify that the proposed NRSMF filter is very efficient for high-density impulse noise removal.

4.2 Analysis on Wide Noise Density

Table 2 provides the PSNR values for peppers (coloured) image (512 × 512) with noise densities varying from 10 to 90%. The values clearly show that there is improvement in PSNR for a wide range of noise density. Figure 8 provides the plot between PSNR and noise density for Lena image, and the result of NRSMF is better than other filters. Figure 7 shows the visual representation for the output image when the image is corrupted by 90% impulse noise. The proposed filter provides a better image quality by retaining the edges, less blurring and low streaking effect.

5 Conclusion

A new NRSMF filter for removing high-density impulse noise is proposed. The proposed NRSMF filter efficiently estimates pixel based on noise density of the image. The NRSMF accurately makes decision according to information in the particular window. Unlike other existing filters, the proposed NRSMF makes sure that there are at least two information pixels in the window for the restoration. Also, a unique technique is used for restoring images corrupted with very high noise densities (over 85%), i.e., the use of pre-processed pixels in the 5 × 5 window for the mean calculation process. The NRSMF shows stable and consistent performance across a wide range of noise densities varying from 10 to 90%. Also, the NRSMF filter performs exceptionally well under very high noise density conditions (85–90%). In addition, the proposed NRSMF provides a good restoration on a large set of greyscale and coloured images.

Table 1. Average PSNR and SSIM values of various filters on Boat, Zelda and Lena image each of size 512 × 512 with varying noise densities (85–99%)

Filters	Metric	Noise density (%)							
		85	87	89	91	93	95	97	99
DBAMF [6]	SSIM	0.732	0.693	0.65	0.5791	0.509	0.401	0.277	0.126
MDBUTM [9]		0.407	0.354	0.305	0.251	0.203	0.152	0.113	0.063
FSBMMF [10]		0.864	0.848	0.827	0.79	0.757	0.697	0.615	0.467
RSIF [11]		0.819	0.798	0.765	0.714	0.671	0.593	0.499	0.345
TVWA [12]		0.905	0.881	0.85	0.771	0.625	0.416	0.201	0.044
ASWMF [13]		0.9	0.885	0.863	0.827	0.749	0.619	0.433	0.197
DAMF [14]		0.907	0.896	0.88	0.856	0.807	0.698	0.455	0.117
Proposed		0.908	0.897	0.883	0.855	0.825	0.773	0.692	0.514
DBAMF [6]	PSNR	21.21	20.66	19.66	18.87	17.91	16.54	15.07	12.09
MDBUTM [9]		17.99	17.16	16.33	15.52	14.65	13.87	13.19	12.35
FSBMMF [10]		25.35	25.06	24.64	23.55	22.77	21.25	19.55	16.7
RSIF [11]		23.7	23.39	22.79	21.62	20.86	19.53	18.16	15.84
TVWA [12]		27.24	26.41	25.32	22.83	19.71	16.15	12.46	8.23
ASWMF [13]		26.6	26.11	25.57	24.57	23.08	21.07	18.67	15.17
DAMF [14]		27.35	26.87	26.36	25.34	23.65	20.47	15.45	8.83
Proposed		27.41	27.07	26.69	25.64	24.7	23.17	21.4	18.16

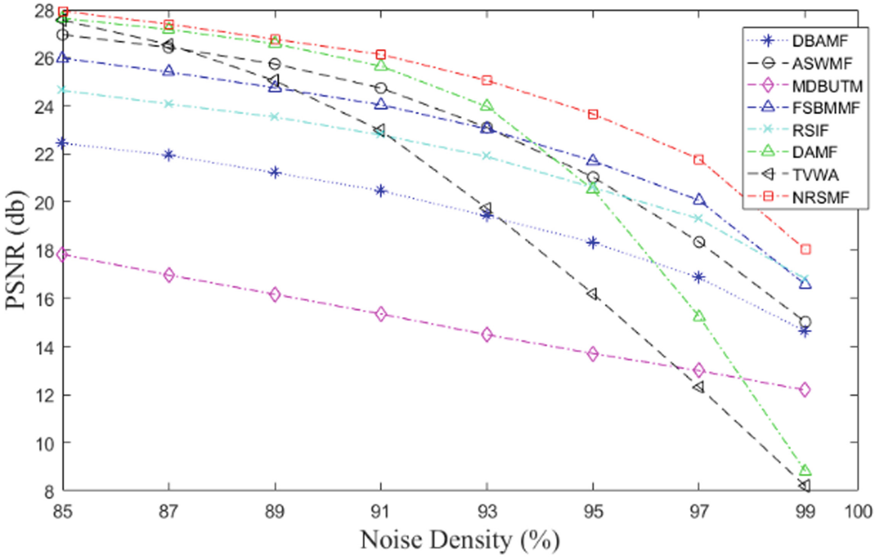

Fig. 5. Average values of PSNR for Boat, Zelda and Lena images (512 × 512) with varying noise densities from 85 to 99%

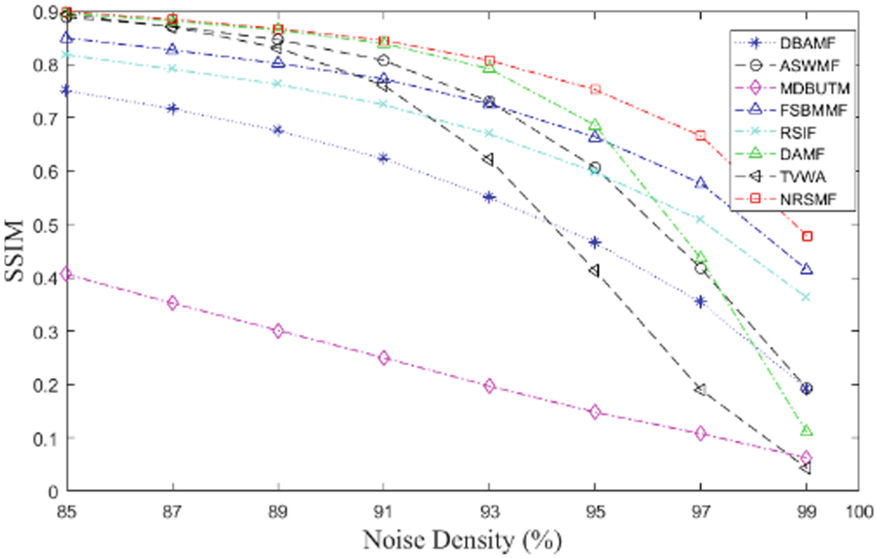

Fig. 6. Average values of SSIM for boat, Zelda and Lena images (512 × 512) with varying noise densities from 85 to 99%

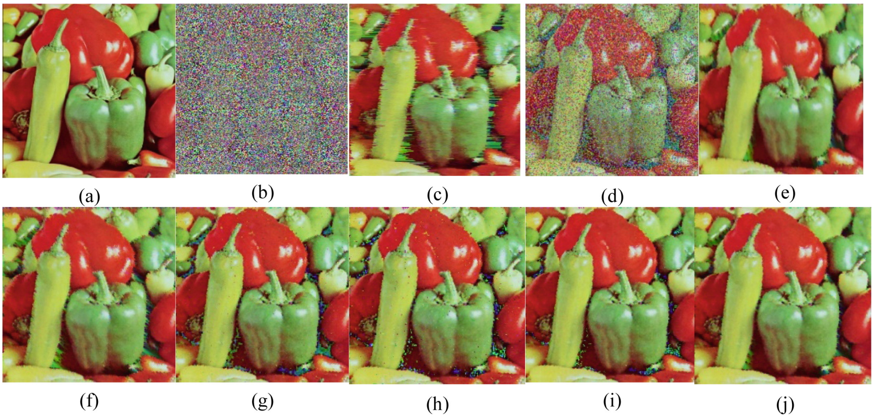

Fig. 7. Simulation results on peppers image (512 × 512) corrupted with 90% salt and pepper noise. **a** original image, **b** noisy image, and restored images from **c** DBAMF [6], **d** MDBUTM [9], **e** FSBMMF [10], **f** RSIF [11], **g** TVWA [12], **h** ASWMF [13], **i** DAMF [14] and **j** NRSMF filters

Table 2. PSNR values of various filters on peppers image (512 × 512) with varying noise densities (10% to 90%)

Filters	Noise density (%)								
	10	20	30	40	50	60	70	80	90
DBAMF [6]	30.52	28.81	27.91	26.42	25.51	24.37	22.98	21.22	18.19
MDBUTM [9]	30.94	29.38	27.82	26.26	24.66	22.77	20.23	17	13.55
FSBMMF [10]	31.69	30.56	29.84	28.26	27.56	26.7	25.66	24.2	21.56
RSIF [11]	31.08	29.87	28.93	27.99	27.01	26.21	25.04	23.5	20.66
TVWA [12]	31.48	30.83	*30.13*	29.44	28.69	27.51	26.04	23.77	19.88
ASWMF [13]	31.29	30.37	29.36	28.24	27.14	26.03	24.75	23.24	20.9
DAMF [14]	30.87	29.88	28.87	27.77	26.77	25.84	24.55	23.04	20.93
Proposed	31.75	31.07	30.13	29.44	28.71	27.87	26.51	25.72	23.71

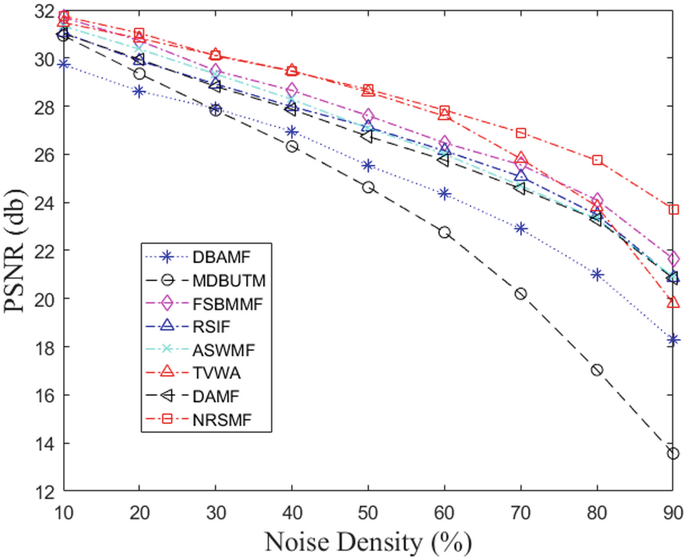

Fig. 8. PSNR values of peppers (512 × 512) image with varying noise densities from 10 to 90%

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