A New Technique for Edge Improved Salt and Pepper Noise Removal

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Abstract **- Filtering impulse noise with edge details preservation is an important task during denoising. In this proposed method if the pixel is detected as a noisy pixel, then it undergoes edge preserving process to detect whether the pixel is a corrupted pixel or edge. This step improves the impulse noise removal especially at higher noise densities using an adaptive window in the filtering process. The performance of the proposed method is compared with the existing decision based median and standard median filter in terms of PSNR and SSIM which showed improved performance**.

Keywords - Denoising,Edgepreserving,Adaptive Median Filtering.

I.INTRODUCTON

The Images are usually corrupted with noises from by various sources. Amongst the various types of noises the impulse noise affects the image during image acquisition and transmission. Impulse noise is independent and uncorrelated to image pixels. The impulse noise is of two types namely the fixed valued impulse noise known as salt and pepper noise; the other one is random valued impulse noise.

In the salt and pepper noise, the noisy pixels take either salt value (255) or pepper value (0) and it appears black and white spots on the images. If p is the total noise density then salt noise and pepper noise will have a noise density of p/2.The mathematical representation of impulse noise is given as:

$$g_{xy} = \begin{cases} 0 \text{ or } 255 \text{ with probability } p \\ f_{xy} \text{ with probability } 1-p \end{cases} \quad \text{----------(1)}$$

Where g_{xy} represents the noisy image pixel, p is the total noise density of impulse noise and f_{xy} is the uncorrupted image pixel. Every time the salt noise and pepper noise may have different noise densities p_1 and p_2 and the total noise density will be $p=p_1+ p_2$.

The two important aspects of image processing are removal of noise and preserving the edge details. Linear and nonlinear filters are used for noise reduction. But nonlinear filter provides better results in reducing impulse noise. The Median filters widely used for preserving the edges and to improve the PSNR values. The linear filters mostly follow a neighborhood averaging mechanism for removing impulse noise. But that tends to destroy all high frequency components like edges in the image, so nonlinear digital filters widely used for removing impulse noise are median filters. Median filters are known for their capability to remove impulse noise as well as preserve the edges. This led to the development of nonlinear median-type filters such as stack filters [4], multistage median [5], weighted median [6,7], rank conditioned median [8], and relaxed median [9]. The main drawback of a standard median filter (SMF) is that it is effective only for low noise densities. At high noise densities, SMFs often exhibit blurring for large window sizes and insufficient noise suppression for small window sizes. The filters designed for image processing are required to yield sufficient noise reduction without losing the high fre-quency content of image edges [13], [16]. However, most of the median filters operate uniformly across the image and thus tend to modify both noise and noise-free pixels. Consequently, the effective removal of impulse often leads to images with blurred and distorted features. Ideally, the filtering should be applied only to corrupted pixels while leaving un-corrupted pixels intact [10]–[12]. Applying median filter unconditionally across the entire image as practiced in the conventional schemes would inevitably alter the intensities and remove the signal details of uncorrupted pixels. Therefore, a noise detec-tion process to discriminate between uncorrupted pixels and the corrupted pixels prior to applying nonlinear filtering is highly desirable.

Decision-based or switching median filters [11], [14] have been proposed with this objective. Possible noisy pixels are identified and replaced with median value or its variant while leaving uncorrupted pixels unchanged. The main drawback of decision-based or switching median filter is that defining a robust decision measure is difficult [12], because the decision is usually based on a predefined threshold value.Although the processing time is less but there occurs a heavy blurring at high noise levels. In order to improve the performance of filtering a new method is proposed. The proposed method has two stages. In the first stage the noisy pixels are identified and in the second stage noise is reduced with edge preservation.

II.PROPOSED METHOD

The proposed method comprises of two parts namely detection stage and second stage wherein noise elimination is undertaken with edge preservation. The detection stage with a 3x3 window size provides a better image detail with relatively low loss of the image information. The Impulse noise is added to the targeted image, and then the noisy pixels are detected with reference to three different conditions. After the detection of noisy pixels they, are subjected to de-noising process. The complete de -noising process is as follows:-

Step One:-

First take smallest size of filtering window i.e., 3X3.

$$g_{xy} = \begin{pmatrix} g_{x-1,y-1} & g_{x-1,y} & g_{x-1,y+1} \\ g_{x,y-1} & g_{x,y} & g_{x-y+1} \\ g_{x+1,y-1} & g_{x+1,y} & g_{x+1,y+1} \end{pmatrix}$$

Step Two:-

The above shown expression has nine elements in filtering window. After excluding the central pixel i.e. $g_{x,y}$, in 3X3 filtering window, then calculate maximum and minimum for the remaining 8 pixel in the filtering window.

$$Min[g] = min\ [g_{x-1,y-1}, g_{x-1,y}, g_{x-1,y+1}, g_{x,y-1}, g_{x-y+1}, g_{x+1,y-1}, g_{x+1,y}, g_{x+1,y+1}]$$

$$Max[g] = max\ [g_{x-1,y-1}, g_{x-1,y}, g_{x-1,y+1}, g_{x,y-1}, g_{x-y+1}, g_{x+1,y-1}, g_{x+1,y}, g_{x+1,y+1}]$$

three conditions arise:

(a) When the value of center pixel lies between max and minvalue of present window then it is termed as noise free pixel.
$Max\ [g] > g_{x,y} > Min[g]$ - (Noise free pixel)

(b) When the value of center pixel is more than maximum orlesser than minimum, then it is termed as noisy pixel.
$g_{x,y} > Max\ [g]$ or $g_{x,yj} < Min\ [g]$ - (Noisy pixel)

(b) When the value of center pixel equals the minimum or themaximum, i.e.
$g_{x,y} = Max\ [g]$ or $g_{x,y\mathbf{j}} = Min\ [g]$

Thereafter determine from center pixel whether it is an edge or a noisy pixel. In this detection process the filtering window would be subdivided to four sub windows, i.e. central column, central row and two diagonals respectively. Afterthencalculate sum of absolute difference between $g_{x,y}$ and its neighbours as follows:

Central Column (m1) = { $g_{x+1,y} - g_{x,y}$} + { $g_{x-1,y} - g_{x,y}$ }
Central Row (m2) = { $g_{x,y-1} - g_{x,y}$} + { $g_{x-y+1} - g_{x,y}$}
Diagonal 1 (m3) = { $g_{x+1,y-1} - g_{x,y}$} + { $g_{x-1,y+1} - g_{x,y}$ }
Diagonal 2 (m4) = { $g_{x+1,y+1} - g_{x,y}$ } + { $g_{x-1,y-1} - g_{x,y}$ }

(d)**T**he minimum value is determined fro 4 sub windows and is termedas pivot point, i.e. M.
v= min [m1, m2, m3, m4]

However: If
v<T1 (30) or v>T2 (230) then

$g_{x,y}$ = Noisy pixel Else
$g_{x,y}$ = Noise-free, and it is an edge.

then median filtering method is used for the noisy pixel. The Denoising step involves following:-

(i) Moving a spatially adaptive window (*w*) of size 3x3 over the noisy image.
(ii) Testing the central pixel of the spatial window to determine whether it is corrupted or uncorrupted.
(iii) A pixel of an image can have values only between 0 and 255. In impulse noise corrupted image the noisy pixels normally obtain minimum or maximum pixel values i.e. either 0 or 255. In case the pixel is non-noisy, then it is unprocessed else, use the adaptive median filter to the pixel. Then, the arithmetic data within this window are calculated which include minimum (*min*), maximum (*max*) and median values (*median*) for the pixels.
(iv) Two prong approaches are applied on the basis of the calculated parameters. if the *median* value lies between the *min* and the *max* pixel values; it is further confirmed that the centre pixel *x(i,j)* also lies within these limits. thereafter when first condition is confirmed , then centre pixel, *x(i,j)* is left unprocessed {*y(i,j) = x(i,j)*} else *x(i,j)* is substituted by the median value {*y(i,j) = median*}; where: *y(i,j)* signifies the restored pixel value. However, if the *median* value does not lie within the *min* and the *max* pixel values; the size of the window (*w*) is adaptively increased by a factor of 2.
(v) Thereafter, the shifting of the spatial window (centering it) to the next pixel in the noisy image. The control then transfers again to the first step, determining the parameters within this incremented window. It is pertinent to mention that the increment in the window size is permitted only to a maximum limit (w_{max}) of 9x9; beyond which the centre pixel will be always replaced by the last processed pixel value.

III.PERFORMANCEMEASURES

The performance of the proposed method is quantitatively estimated using the parameters Peak Signal to Noise Ratio (*PSNR*) in dB and Structural Similarity Index (*SSIM*).

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

$$MSE = \frac{\sum_{ij}(r_{ij} - x_{ij})^2}{MN}$$

Where

r	- original image
x	-restored image
MN	-size of the original image

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

where

μ_x	-Average of x
μ_y	-Average of y
σ_x^2	-Variance of x
σ_y^2	-Variance of y
σ_{xy}	-covariance of x and y

$C_1=(k_1L)^2, C_2=(k_2L)^2$

Where

L=dynamic range (L=255)

$k_1=0.01$ and $k_2=0.03$

IV .RESULTS AND DISCUSSIONS

The proposed filter is tested using 256×256, 8-bits/pixel gray scale high detailed image of Barbara, Lena, Cameraman and Baboon as input images .The images are corrupted by impulse noise at various densities.

For qualitative analysis, performances of the filters are tested at different levels of noise densities, and the results are shown in Figs. 1. In Fig. 1, the first column represents original images, and the second column represents noisy images at different densities. Subsequent columns represent the processed images for SMF, DMF, and PA respectively.

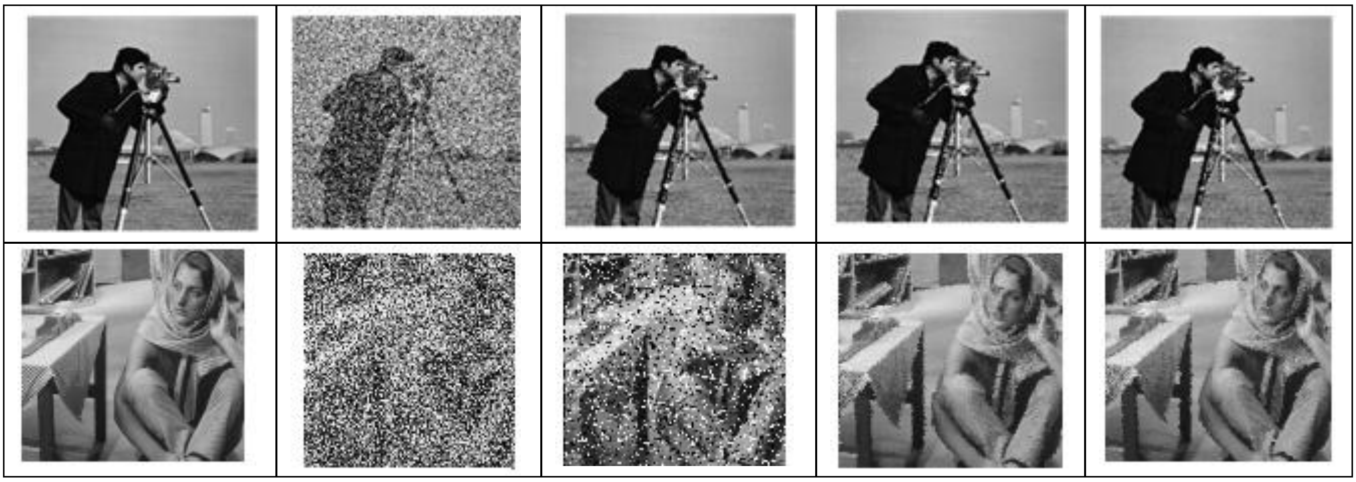
To show the individuality of the proposed algorithm, experiments are carried out on low, medium and high detailed standard images. All images are grayscale with intensity values in the range of [0, 255]. Images are of size 256×256.

Fig. 1 shows comparison among the repaired images obtained by standard, SMF(3X3), DMF [1],and the proposed filter in this paper. The performances in terms of *PSNR* and *SSIM* for all the above mentioned algorithms are shown inTable I and II, III and IV respectively.

Table I shows computed values of *PSNR* and *SSIM* for the cameraman image at all noise levels. Similarly Table II shows the values for Barbara image, Table III for Lena image and Table IV for Baboon image. It is clear from the Tables at all noise levels the performance the proposed filter overtakes the present one. The qualitative analysis from Fig. 1 proves that the levelof impulse noise is considerably reduced and the picturing is also improved to a great extent in the reconstructed images. For higher noise density level (50%-90%), the performance of the proposed filter is preserving the details of the image along with suppression of noise.

V.CONCLUSION

This paper proposes an adaptive median filtering with edge preservation for suppression of impulse noise at high noise intensities; without incorporation of difficult optimization techniques. The proposed approach performs decision to edge or noisy pixel and for the noisy pixel; the window size is depending upon the number of corrupted pixels within the local window to a maximum of 9x9. The results show that the proposed filter recommends an effective improvement in the performance across a wide range of noise densities in comparison with other filtering approaches.



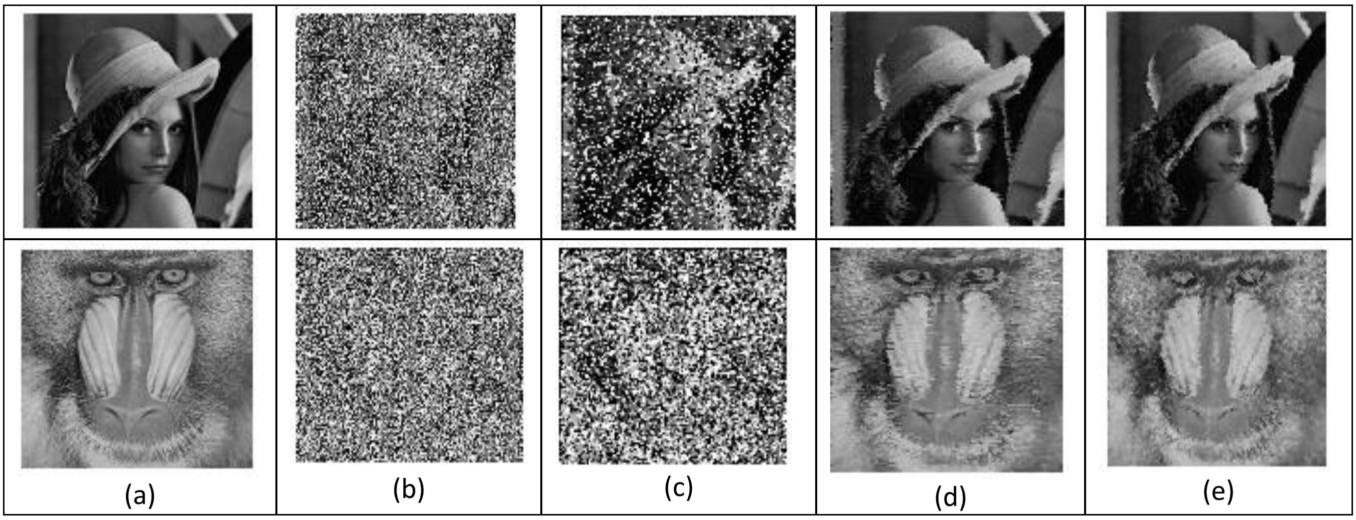


Fig 1.Simulation results of different filters column. (a) Original image. (b) Noisy corrupted image. (c) Output for SMF. (d) Output for DMF. (e) Output for PA. Row 1 shows the cameraman image corrupted by 50% noise. Row 2 shows the barbaral image corrupted by 60% noise. Row 3 shows the Lena image corrupted by 70% noise. Row 4 shows the baboon image corrupted by 80% noise.

Impulse Noise Density	PSNR			SSIM		
	SMF	DMF	PA	SMF	DMF	PA
10%	25.934	30.373	34.08	0.947	0.998	0.999
20%	24.142	28.538	30.048	0.889	0.997	0.998
30%	20.57	27.003	28.06	0.879	0.996	0.998
40%	17.427	25.335	26.02	0.869	0.994	0.996
50%	14.282	23.623	24.29	0.860	0.992	0.995
60%	11.724	22.55	23.49	0.853	0.990	0.991
70%	9.434	21.00	22.327	0.815	0.980	0.989
80%	7.757	19.328	21.00	0.800	0.960	0.985
90%	6.186	17.225	18.231	0.662	0.950	0.980

Table I PSNR and SSIM for cameraman at different noise intensites

Table II PSNR and SSIM for Barbara image at different noise intensites

Impulse Noise Density	PSNR			SSIM		
	SMF	DMF	PA	SMF	DMF	PA
10%	27.861	32.52	36.625	0.995	0.998	0.999
20%	25.697	31.059	33.01	0.989	0.997	0.998
30%	21.801	29.29	30.245	0.969	0.995	0.998
40%	18.084	27.67	28.277	0.959	0.991	0.997
50%	15.023	25.938	26.530	0.927	0.986	0.997
60%	12.028	24.433	24.77	0.918	0.972	0.996
70%	9.80	22.435	23.433	0.895	0.934	0.995
80%	8.059	20.699	21.596	0.844	0.925	0.990
90%	6.618	17.663	19.791	0.789	0.899	0.980

Table III PSNR and SSIM for lena image at different noise intensites

Impulse Noise Density	PSNR			SSIM		
	SMF	DMF	PA	SMF	DMF	PA
10%	31.616	36.19	39.48	0.88	0.997	0.999
20%	27.511	34.25	35.29	0.83	0.994	0.998
30%	22.649	31.44	32.262	0.789	0.993	0.994
40%	18.566	29.18	30.145	0.728	0.99	0.991
50%	14.41	27.558	28.623	0.69	0.985	0.989
60%	11.661	26	27.021	0.659	0.982	0.985
70%	9.26	23.83	25	0.637	0.945	0.983
80%	7.42	21.101	23.05	0.6	0.882	0.958
90%	5.789	18.014	20.7	0.577	0.843	0.943

Table IV PSNR and SSIM for Baboon image at different noise intensites

Impulse Noise Density	PSNR			SSIM		
	SMF	DMF	PA	SMF	DMF	PA
10%	27.861	32.52	36.625	0.995	0.998	0.999
20%	25.697	31.059	33.01	0.989	0.997	0.998
30%	21.801	29.29	30.245	0.969	0.995	0.998
40%	18.084	27.67	28.277	0.959	0.991	0.997
50%	15.023	25.938	26.530	0.927	0.986	0.997
60%	12.028	24.433	24.77	0.918	0.972	0.996
70%	9.80	22.435	23.433	0.895	0.934	0.995
80%	8.059	20.699	21.596	0.844	0.925	0.990
90%	6.618	17.663	19.791	0.789	0.899	0.980

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