High Density Impulse Noise Removal Using Modified Switching Bilateral Filter

T. Veerakumar, S. Esakkirajan, and Ila Vennila

***Abstract*—**In this paper, we propose a modified switching bilateral filter to remove impulse noise and enhance the image details in an image. The proposed filter consists of noise detection stage and noise reduction stage. The noise detection is based on the gray level [Lmin, Lmax]. The noise reduction is based on the global trimmed mean with modified switching bilateral filter. This modified switching bilateral filter effectively removes the salt and pepper noise at very high noise density. Simulation results show that our proposed filter achieves high peak signal to noise ratio, Image Enhancement factor and correlation factor. Even though the time complexity of proposed filter is greater than the other impulse noise filters, the performance of the proposed filter with respect to noise removal is better than the existing filters.

***Keywords*—** Bilateral filter, Impulse noise, Global trimmed mean, Noise detection, Noise reduction, Switching Bilateral filter.

I. Introduction

During image acquisition, amplification and transmission, the images are degraded by noise [1]. An important crisis of image denoising is to effectively eliminate noise from an image while keeping its information. Noise removal is difficult task because images may be corrupted by different types of noise, such as additive, impulse or signal dependent noise [2]. Linear filter can be used to remove additive noise in an image. However, linear filtering blur edges and it fails to minimize impulse noise. This drawback leads to the use of non-linear filtering in impulse noise reduction [3]. In this paper, we propose a new filtering scheme that can remove the impulse noise. The impulse noise is characterized by replacing a part of image pixels with noise values, leaving the remainder unaffected. Nonlinear filters have been developed for removing impulse noise such as the traditional median filter [13]. Extensions of the median filter [4-6, 7, 8, 9-10, 11-13,14] are developed to meet various criteria, e.g., robustness, preservation of edge. The advanced algorithms for noise removal aim at preserving edges and details in images while removing noise [15].

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Tomasi and Manduchi propose a bilateral filter that uses weights based upon spatial and radiometric similarity [16]. The bilateral filter has good results in removing noise while preserving image details. Also, this method is non-iterative, local and simple [16]. Extensions of bilateral filtering such trilateral [17] and switching bilateral filter [18] can be used to preserve details in an image. The trilateral filter is an extension of the bilateral filter with incorporated rank-order absolute difference statistics for impulse noise detection [17]. This method will fail if half of the pixels in the processing window are corrupted [18]. The switching bilateral filter based upon the “detect and replace” methodology. Noise detection is based on the absolute difference between a current pixel and value and the reference median. The reference median is obtained from sorted quadrant median vector (SQMV) [18]. The computation of reference median value is complex one. In the case of salt and pepper noise, the noisy pixels are either ‘0’ or ‘255’. In this paper, we propose a modified switching bilateral filter, which is based on the global trimmed mean value instead of reference median value and the weights of the bilateral filter is based on the noise free pixels alone. But, in bilateral and switching bilateral filters weights depends on both noisy and noise free pixels in the window. The modified switching bilateral filtering removes the noise and enhances the fine details in an image, by means of a nonlinear combination of nearby noise free pixel and global trimmed mean value.

This paper organized as follows. In section II deals with the computation of global trimmed mean value. The modified switching bilateral filter is discussed in section III. Section IV demonstrates the simulation results of the proposed filter. Finally, conclusion is given in section V.

II. Estimation of Global trimmed mean

A. Noise Model

In the classical salt and pepper impulse noise model, the observed noisy image f(x,y) is given by

$$f(x,y)=\begin{cases} L_{\min}, & with\ probability\ p \\ L_{\max}, & with\ probability\ q \\ O(x,y) & with\ probability\ r \end{cases} \quad (1)$$

where O denotes noise free pixels, r = 1 - (p+q). p+q is the noise level. L_{min} is lowest luminance of the gray value in an image. L_{max} is the largest luminance of the gray value in an image.

B. Computation of Global Trimmed Mean Value

The method to obtain trimmed global mean is summarized below:

(a) The image $g(x, y)$ is obtained from $f(x, y)$ by removing all the noisy pixel.

(b) The trimmed global mean (M) of the noise free image $g(x, y)$ is calculated as

$$M = \frac{1}{N}\sum_{i \in N} \hat{g}(i) \tag{2}$$

where N is the number of noise free pixel in an image and $\hat{g}$ is the noise free element in an image. The block diagram of computation of global trimmed mean value is shown in figure 1.

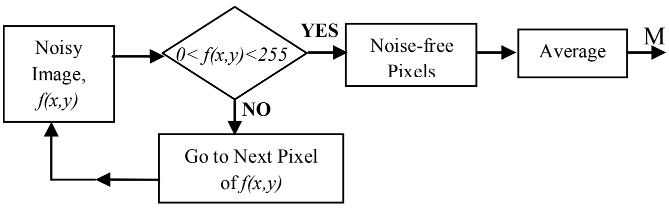


Fig. 1 Block diagram of computation of global trimmed mean value

III. MODIFIED SWITCHING BILATERAL FILTER

A. Bilateral Filter

Tomasi and Manduchi [16] proposed the bilateral filter, which is a nonlinear one. This filter removes Gaussian noise while preserving image details. Weighted average of the neighborhood gray level in the selected window replaces each noisy pixel. The weighting function gives high priority to those pixels that are both near the processing pixel and similar to the processing pixel.

Let f(x,y) be the current processing pixel, and the neighborhood pixels are denoted as f(x+s,y+t). Here, s and t is varying from –N to N, N is the size of the selected window. The output of bilateral filter $\hat{f}(x, y)$ is defined as

$$\hat{f}(x, y) = \frac{\sum_{s=-N}^{N}\sum_{t=-N}^{N} W_G(s,t) W_R(s,t) f(x+s, y+t)}{\sum_{s=-N}^{N}\sum_{t=-N}^{N} W_G(s,t) W_R(s,t)} \tag{3}$$

where

$$W_G(s,t) = \exp\left(-\frac{(x-s)^2 + (y-t)^2}{2\sigma_S^2}\right) \tag{4}$$

and

$$W_R(s,t) = \exp\left(-\frac{(f(x,y) - f(x+s, y+t))^2}{2\sigma_R^2}\right) \tag{5}$$

The bilateral filter effectively removes the Gaussian noise at the same time retain the image details, but it is fails to remove impulse noise [18]. Because the noisy pixel is very different from its neighbors, the surrounding weights are very small to change the noisy pixel in the range filter [16].

B. Switching Bilateral Filter

The switching bilateral filter [18] proposed by C. H. Lin et al, is a nonlinear filter which removes both Gaussian and impulse noise while preserving image details. This filter consist of two stages, in first stage to detect the type of noise then apply the filtering to the noisy pixel is a second stage.

Let f(x,y) be the current processing pixel, and the neighborhood pixels are denoted as f(x+s,y+t). Here, s and t is varying from –N to N, N is the size of the selected window. The output of switching bilateral filter $\hat{f}(x, y)$ is defined as

$$\hat{f}(x, y) = \frac{\sum_{s=-N}^{N}\sum_{t=-N}^{N} W_G(s,t) W_{SR}(s,t) f(x+s, y+t)}{\sum_{s=-N}^{N}\sum_{t=-N}^{N} W_G(s,t) W_{SR}(s,t)} \tag{6}$$

where

$$W_{SR}(s,t) = \exp\left(-\frac{(I - f(x+s, y+t))^2}{2\sigma_R^2}\right) \tag{7}$$

and

$$I = \begin{cases} SQMR, & \text{Im}\,\textit{pulse noise} \\ f(x,y) & \textit{Gaussian noise} \end{cases} \tag{8}$$

The computation of sorted quadrant reference median (SQMR) value is given in [18]. In this method, the range filter (WSR) depends upon all the pixels in the selected window such as both noisy and noise free pixels. The computation of SQMR is more complex because it has to be computed for each and every processing pixel.

C. Modified Switching Bilateral Filter

In this section, we propose a new noise removal algorithm: the modified switching bilateral filter which is intended for impulse noise removal. The impulse noise generally replaces the noise free pixel by noisy pixel (i.e) not all the pixels are affected by impulse noise. This characteristic is used to compute the WMSR which results in improved noise reduction as well it preserves the image details. Let f(x,y) be the current processing pixel, and let f(x+s,y+t) be the (N x N) neighborhood pixels of f(x,y).

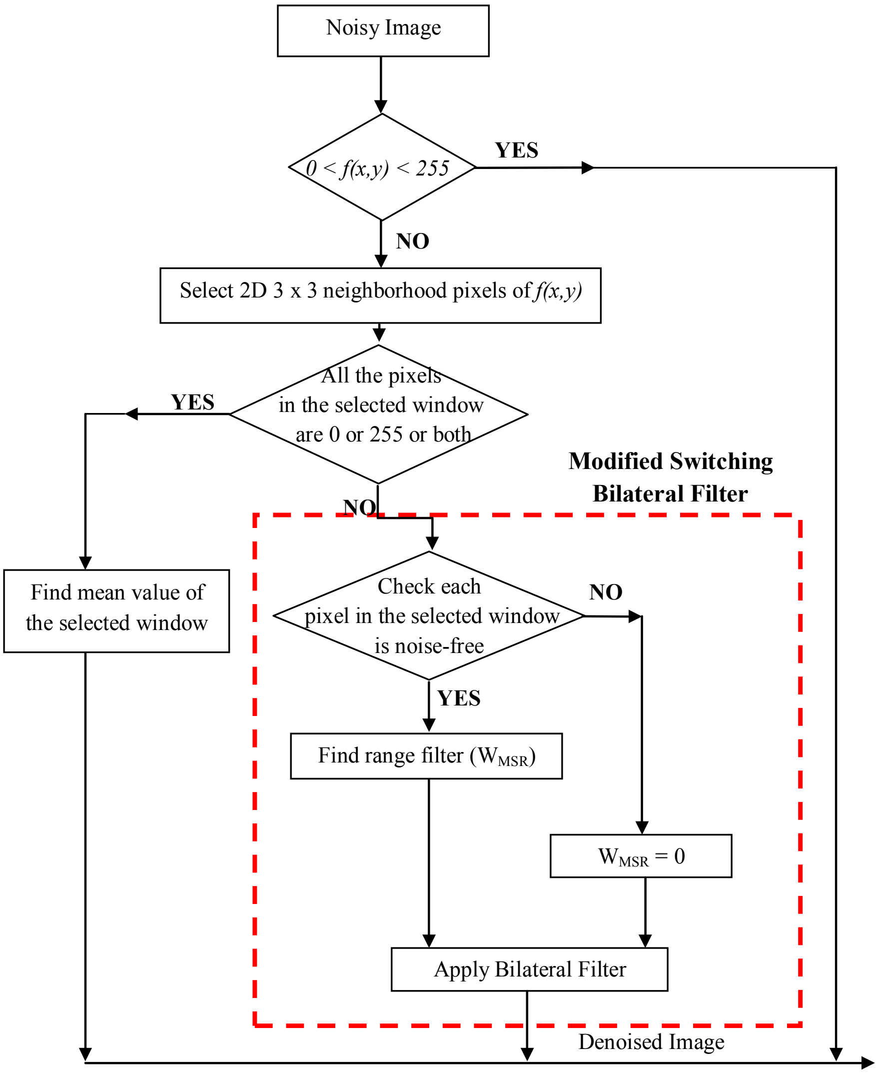


Fig. 2. Flowchart of modified switching bilateral filter

The modified switching bilateral filter is defined as

$$\hat{f}(x,y)=\frac{\sum_{s=-N}^{N}\sum_{t=-N}^{N}W_G(s,t)W_{MSR}(s,t)f(x+s,y+t)}{\sum_{s=-N}^{N}\sum_{t=-N}^{N}W_G(s,t)W_{MSR}(s,t)} \tag{9}$$

where

$$W_{MSR}(s,t)=\begin{cases}\exp\left(-\dfrac{(M-f(x+s,y+t))^2}{2\sigma_R^2}\right) & for\, f(x+s,y+t)\notin noisy\,pixel \\ 0 & Otherwise\end{cases} \tag{10}$$

and M denotes the global trimmed mean value. This filter is simple and the calculation of modified range filter is depends only on the noise free pixels in the neighborhood. The global trimmed mean value is computed with the noise free pixel. The performance of the proposed algorithm is better due to the fact that the computation of WMSR is based on noise free pixel, and also it takes into account the correlation between neighboring noise free pixels. The denoised image obtained using the proposed algorithm is better than the bilateral and switching bilateral filters. The flow chart of the modified switching bilateral filter is shown in figure 2.

IV. Results and Discussion

Simulation of proposed algorithm is carried out in various test images: ‘Lena’, ‘Boat’, and ‘Bridge’. All the images with the size of 512 x 512 8 bit gray scale images corrupted with salt and pepper noise with wide range of noise densities from 10 to 95%. The simulation is carried out in MATLAB 7.0.1 environment with Pentium Duo core-2.80GHz with 1GB of RAM. Qualitative and quantitative performance of proposed algorithm is on par with the existing algorithms. The qualitative measures taken into consideration are Peak Signal to Noise Ratio (PSNR), Image Enhancement Factor (IEF) and Correlation Factor (CF). The PSNR in dB is defined as

$$PSNR=10\log_{10}\left(\frac{255^2}{MSE}\right) \tag{11}$$

where $MSE = \dfrac{\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}\left(O(x,y)-\hat{f}(x,y)\right)^2}{M \times N}$, MSE stands for Mean Square Error, O(x,y) is the original image, $\hat{f}(x,y)$ represents the denoised image, and $M \times N$ is the size of the image.

The performance of the filter has been studied by computing image enhancement factor (IEF), which is defined as

$$IEF = \frac{\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}\left(f(x,y)-O(x,y)\right)^2}{\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}\left(\hat{f}(x,y)-O(x,y)\right)^2} \tag{12}$$

where $f(x,y)$ represents noisy image.

The correlation factor is widely used in statistical analysis, pattern recognition, and image processing. The correlation factor (R) is defined as

$$R = \frac{\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}\left(\hat{f}(x,y)-\bar{\hat{f}}\right)\left(O(x,y)-\bar{O}\right)}{\sqrt{\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}\left(\hat{f}(x,y)-\bar{\hat{f}}\right)^2\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}\left(O(x,y)-\bar{O}\right)^2}} \tag{13}$$

where $\bar{\hat{f}}$ is mean value of the denoised image, and $\bar{O}$ is the mean value of the original image.

A. Quantitative Measure

The PSNR value of the proposed algorithm is on par with the existing algorithms by varying the noise density from 10% to 95% , which is shown in table 1. From the table it is possible to infer that the proposed algorithm gives better PSNR values than the existing algorithms. Higher PSNR value is obtained due to the fact that the proposed algorithm effectively preserves the fine details of the image even if it is corrupted by high density noise. At high noise density, the proposed algorithm gives a PSNR value which is almost 2 to 4 dB better than the existing algorithms.

To validate the performance of the proposed algorithm correlation factor is also taken into consideration. This factor gives the correlation between the input image and denoised image, which is shown in table 2. The maximum value of the correlation factor is 1, which means both images are perfectly matched. From the table, it is evident that the proposed algorithm, gives good match between input and denoised image than the other existing algorithms at high noise density.

Denoising performance is quantitatively measured by image enhancement factor (IEF). The IEF values of the proposed algorithm and existing algorithms are given in table 3. Form the table; it is possible to observe that the proposed algorithm gives better results than the existing algorithms of noise density greater than 40%. The proposed algorithm preserves fine details in the image which is better than the existing denoising algorithms.

The proposed algorithm is also tested with Boat and Bridge images and their results are shown in figure 3 and figure 4 respectively. From the figure, it is evident that the performance of the proposed algorithm is better than the existing algorithms.

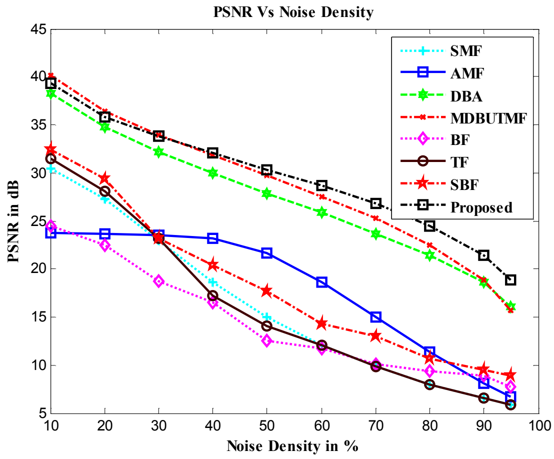


Fig. 3 Performance PSNR curves of Boat Image

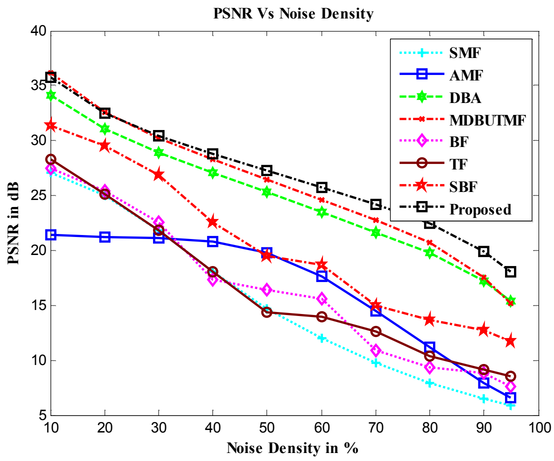


Fig. 4 Performance PSNR curves of Bridge Image

B. Selection of σ_S and σ_R

Two parameters of interest in Bilateral filter are σ_S and σ_R. These parameters are not optimal for all images. In this approach, the values of σ_S and σ_R are chosen as 1 and 60 respectively. The performance of the various values of σ_S and σ_R versus PSNR for Lena image which is corrupted by 50% salt and pepper noise is shown in figure 5.

Table 1 PSNR results of Lena Image

Method	PSNR in dB									
	10%	20%	30%	40%	50%	60%	70%	80%	90%	95%
SMF	31.71	28.33	23.58	18.92	15.24	12.36	10.00	8.12	6.63	6.00
AMF	25.19	25.16	25.01	24.46	22.78	19.31	15.25	11.54	8.22	6.77
DBA	40.39	36.35	33.92	31.72	29.82	27.52	25.32	23.06	19.57	16.88
MDBUTMF	41.62	38.02	35.57	33.47	31.67	29.46	27.26	24.46	20.06	16.53
BF	22.96	20.76	19.85	17.73	15.59	12.80	10.11	8.54	6.02	5.78
TF	32.03	29.03	25.45	17.43	16.86	14.73	13.84	12.65	10.45	10.23
SBF	37.65	35.60	31.22	28.48	24.90	20.51	19.20	18.00	16.82	15.27
Proposed	40.97	37.61	35.35	33.51	31.94	30.26	28.48	26.18	22.97	20.32

Table 2 Correlation factor of Lena image

Method	Correlation Factor									
	10%	20%	30%	40%	50%	60%	70%	80%	90%	95%
SMF	0.99	0.98	0.94	0.84	0.69	0.53	0.36	0.22	0.10	0.05
AMF	0.96	0.96	0.96	0.95	0.93	0.85	0.67	0.47	0.22	0.11
DBA	1 .0	1.0	0.99	0.99	0.99	0.97	0.96	0.93	0.84	0.71
MDBUTMF	1.0	1.0	1.0	0.99	0.99	0.98	0.97	0.95	0.85	0.64
BF	0.71	0.55	0.43	0.33	0.25	0.19	0.13	0.09	0.04	0.02
TF	0.99	0.98	0.96	0.53	0.45	0.39	0.23	0.19	0.14	0.08
SBF	0.99	0.99	0.98	0.94	0.92	0.87	0.75	0.70	0.51	0.41
Proposed	1.0	1.0	1.0	0.99	0.99	0.99	0.98	0.97	0.93	0.86

Table 3 IEF results of Lena image

Method	IEF									
	10%	20%	30%	40%	50%	60%	70%	80%	90%	95%
SMF	42.31	38.46	19.33	8.93	4.76	2.94	2.00	1.48	1.18	1.08
AMF	9.43	18.55	26.87	31.95	27.00	14.58	6.70	3.26	1.71	1.29
DBA	311.74	243.94	208.93	170.12	136.61	96.54	68.10	46.15	23.31	13.24
MDBUTMF	415.31	357.69	305.15	254.69	209.48	151.05	106.40	63.75	26.09	12.20
BF	1.0303	1.0299	1.0297	1.0293	1.0292	1.0288	1.0286	1.0284	1.0283	1.0281
TF	82.31	78.46	69.33	58.93	44.76	32.94	22.00	11.48	5.18	1.02
SBF	323.70	305.43	270.34	226.87	201.62	141.82	98.99	54.61	23.99	10.33
Proposed	356.80	325.38	290.12	256.58	222.62	181.52	140.80	94.68	50.92	29.23

Table 4 Computational time for denoising algorithms

Method	Computational time in sec		
	Lena	Boat	Bridge
SMF	0.1292	0.1394	0.1290
AMF	64.7435	66.9690	64.0814
DBA	5.6810	5.6215	5.6269
MDBUTMF	29.5819	31.5522	29.5883
BF	8.4724	8.7910	10.1774
TF	12.5732	12.9534	12.6314
SBF	58.6048	60.6733	58.3992
Proposed	51.9800	57.5440	55.0708

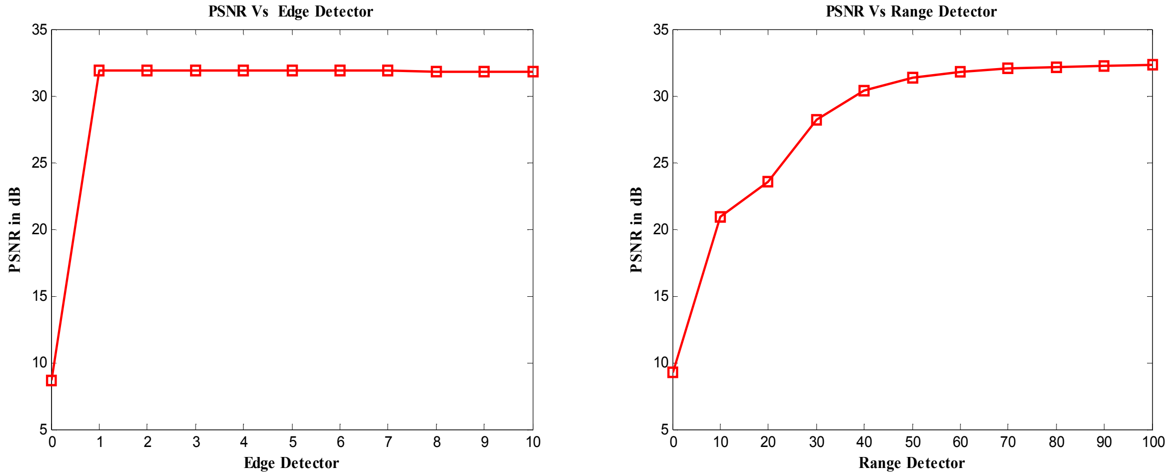
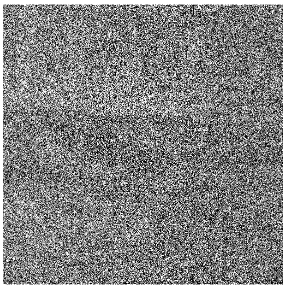
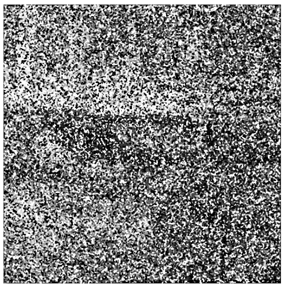


Fig. 5 Performance curve of PSNR Vs Edge and Range Detector

(a) Original Image

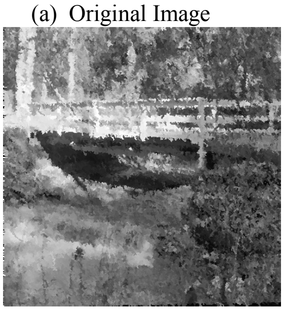


(b) 80% Noisy Image

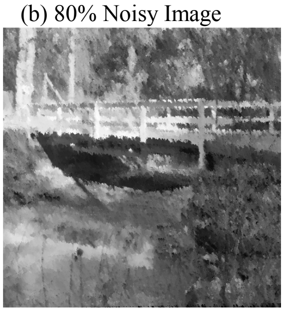


(c) SMF

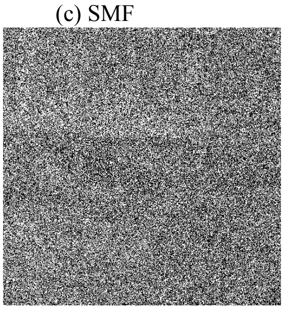
(d) AMF



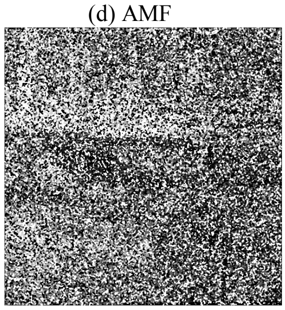
(e) DBA



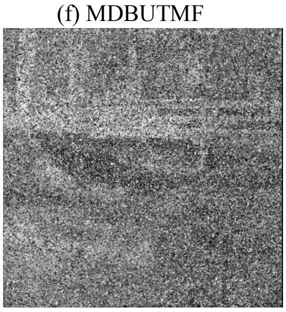
(f) MDBUTMF



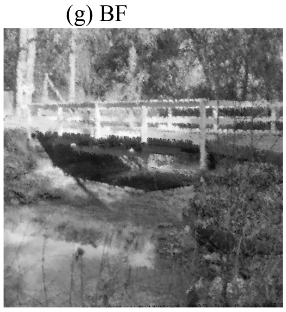
(g) BF



(h) TF



(i) SBF



(j) Proposed

Fig. 6 Results of different algorithms for Bridge image

From the figure, it is possible to observe that even if the edge detector σ_S is greater than one the PSNR value remains the same. Hence, the edge detector σ_S is taken as one for salt and pepper noise affected image. Similarly, the plot of PSNR versus range detector (σ_R) for Lena image with 50% noise density is shown in figure 5. From the figure, it is possible to ensure that the PSNR value is not changing drastically for the value σ_R greater than 60. Hence, σ_R is chosen as 60.

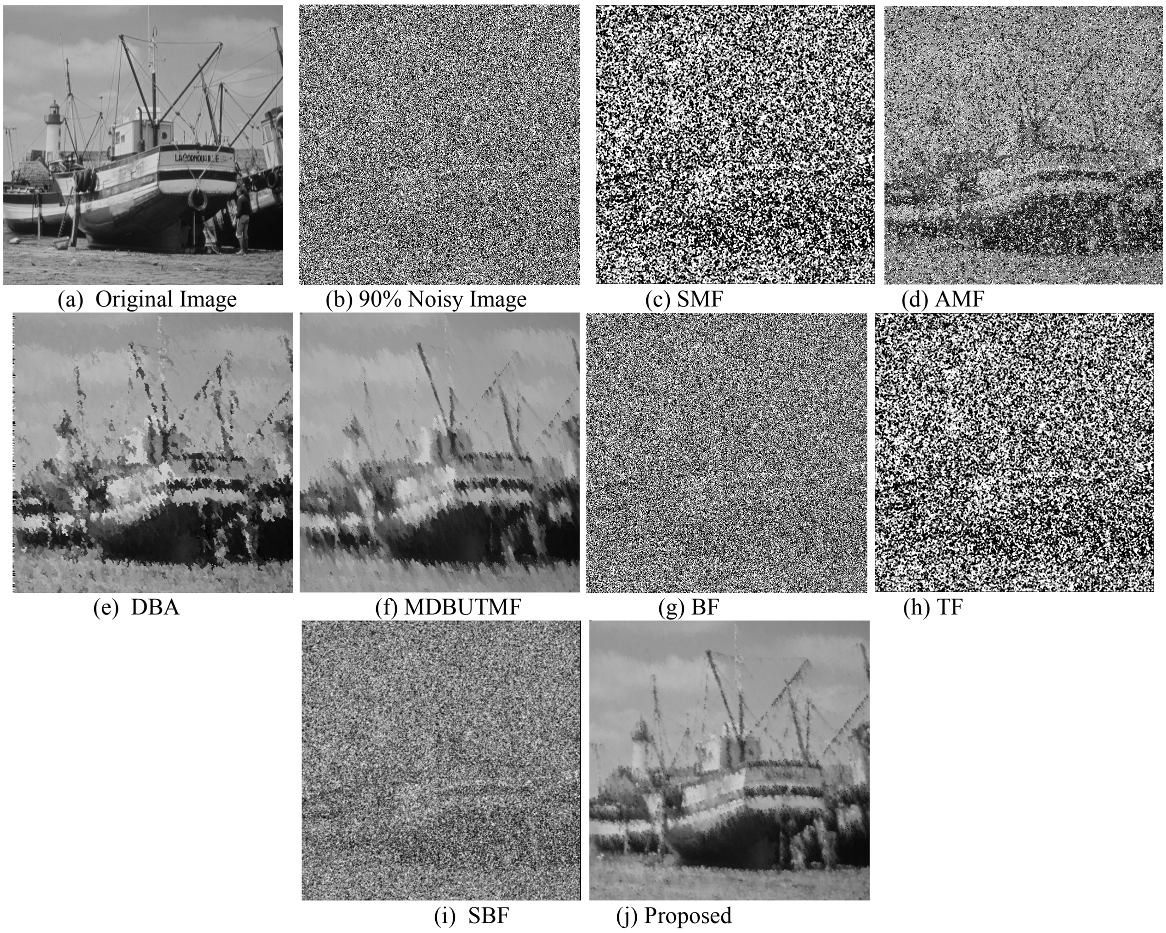


Fig. 7 Results of different algorithms for Boat image

A. *Qualitative Measure*

The qualitative analysis of the proposed algorithm against the existing algorithms for Bridge and Boat images are shown in figure 6 and 7 respectively. Bridge and Boat images are corrupted with 80% and 90% salt and pepper noise respectively. From the figures, it is possible to observe that the visual quality of the denoised image obtained using the proposed algorithm is better than the existing algorithms. The proposed algorithm effectively removes the salt and pepper noise and efficiently retains the fine details of the image.

B. *Computational complexity*

The computation time of the proposed and the existing algorithm for different test images with 90% noise density is given in table 4. From the table, it is evident that the computational time of the proposed algorithm is much higher than the existing algorithms. This is due to the fact that the global trimmed mean value has to be computed first, and then this value is used to compute WMSR for every processing pixel. The computational time of the proposed algorithm is less than the switching bilateral filter and it higher than other existing algorithm like Median filter and its variants.

V. CONCLUSIONS

In this paper, a new impulse noise removal algorithm is proposed. The proposed algorithm effectively removes the salt and pepper noise and efficiently retains the fine details of the original image. At high noise density, PSNR value of the proposed algorithm is almost 2 to 4dB better than the existing algorithms. The edge detector is used to enhance the fine details due to edge preserving properties of bilateral filter and the range detector is efficiently removes the noise pixel by the property of nonlinear combination of noise free pixels in the neighbors. The correlation factor of the proposed algorithm is far better than the existing algorithm at medium and high noise density. Even though the computation time of the proposed algorithm is higher than the popular median filter and its variants, suitable optimization technique can be used to reduce the computation time.

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