Impulse Noise Detection and Filtering in Switching Median Filters

Ashima Mittal
Indira Gandhi Institute of Technology, Delhi, India

Akash Tayal
Indira Gandhi Institute of Technology, Delhi, India

ABSTRACT
The switching median filter has proved to be quite effective in removing impulse noise. Noise detection plays a significant role in filtering. The proposed algorithm consists of two iterations for detecting noisy pixels. An exhaustive list of simulation results for various types of images shows that the peak signal to noise ratio of the proposed algorithm is high compared to the existing algorithms.

General Terms
Noise detection and removal

Keywords
Impulse noise, peak signal to noise ratio, switching median filter.

1. INTRODUCTION
The degradation of impulse noise has been removed by median filters [1]-[3]. The switching median filters classify the pixel as corrupted or uncorrupted. Only after classifying the pixel as corrupted, they replace the pixel with the median of its surrounding pixels. They outperform median filters where no switching is used and each pixel, whether corrupted or not is replaced with the median of its neighbouring window. Various switching median filters have been proposed [4]-[10].

The algorithm proposed in [7] utilises the convolutionary kernels for the detection of impulse noise. It convolves the degraded image with four kernels and uses the minimum of the result to classify the pixel as noisy. Once the pixel is classified as impulse, it is replaced with the median of its surrounding pixels. The algorithm proposed in [9] is based on alpha trimmed mean for the detection of impulse noise. The BDND detector proposed in [8] plays a significant role in removal of impulse noise up to 90%. It utilises two iterations to classify the pixel as corrupted or uncorrupted. The first iteration considers a 21×21 neighbourhood. Once the pixel is classified as corrupted in first iteration, it is examined under second iteration by considering a 3×3 neighbourhood. It accurately determines two boundaries to classify the pixels in three groups- lower intensity, uncorrupted and higher intensity. The algorithm proposed in [10] detects the noisy pixels via two iterations. The first iteration is based on BDND detector and the second iteration utilises convolutionary kernels to classify the pixel as noisy.

In this letter, we propose a new and simplified algorithm for detection of impulse noise. The algorithm consists of two iterations. The first iteration utilises the concept of BDND detector with slight modification. It classifies the pixel as corrupted or un-corrupted by examining it in 21×21 neighbourhood. The second iteration utilises the fundamental property of impulse noise for detection. Extensive simulation results show that the proposed algorithm shows better peak signal to noise ratio both for colored and gray scale images compared to the other existing algorithms. The proposed algorithm is relatively easy and works for noise density up to 90%. The strength of our algorithm lies in the fact that it gives amazingly good results with very less and simplified lines of code.

The rest of the letter is organized as follows. Section 2 provides a detailed analysis of our proposed method. Section 3 describes the extensive simulation results done on three colored images depicting the improvement of peak signal to noise ratio by our proposed method. Finally, Section 4 concludes the proposed method.

2. THE PROPOSED ALGORITHM
Like [10], our proposed method consists of two iterations. The first iteration tests the pixels via modified BDND algorithm. Once the pixel is considered to be corrupted in first iteration, it is piped into the second iteration. The proposed algorithm consists of the following steps:

1. Set the variable flag and flag1 of all the pixels as 1. Consider a 21×21 window around the center pixel x_{ij}.
2. Take the square root of the various pixels lying in the window and arrange them in sorted order in vector v_o.
3. Compute the median med of the vector v_o.
4. Calculate the difference between the adjacent pixels in the vector v_o and label it as difference vector v_d.
5. For the interval $[0, med]$, find the pixels corresponding to the maximum value in vector v_d and label the square of the corresponding pixel in v_o as b_1. Similarly find the boundary b_2 for the interval $[med, 255]$.

6. Classify the pixels in the current window in three clusters. If the pixel x_{ij} under consideration belongs to the middle cluster, it is considered as uncorrupted else it is considered as corrupted. If the pixel is considered to be corrupted, set its flag i.e. $flag_{ij}$ to 0 and pass it in second iteration.
7. In second iteration, impose a 5×5 window around the pixel x_{ij}. Sort all the pixels in this window and label the sorted vector as Dr . Compute the median med_{ij} of the vector Dr. If the pixel x_{ij} satisfies the equation $Dr(s) < x_{ij} < Dr(t - s + 1)$, set the flag1 of the pixel x_{ij} i.e. $flag1_{ij}$ as 0 else set it as 1. Here t represents the number of pixels in the current window and s is taken as 2 to optimize the results. The idea in second iteration is inspired from [9] with modifications.
8. Once the pixel detection is done, it is refined by a fairly simple equation listed below for switching median filters. Flag1 variable decides whether the pixel x_{ij} is corrupted or uncorrupted.

   $$x_{ij} = flag1_{ij} \times med_{ij} + (1 - flag1_{ij}) \times x_{ij}$$

   The modified value of x_{ij} is taken for refinement of subsequent pixels to improve results.

The testing images are shown in fig1. The various algorithms that are used for comparison with our method outline the detection algorithm for the detection of various noisy pixels. Once the detection has been done by these methods, we have used the following general equation of switching median filter for the filtering to compute the peak signal to noise ratio for the various algorithms.

$$x_{ij} = flag_{ij} \times med_{ij} + (1 - flag_{ij})x_{ij}$$

The variable flag indicates whether the pixel is noisy or non-noisy. The value of flag is different for different algorithms used in our comparison.

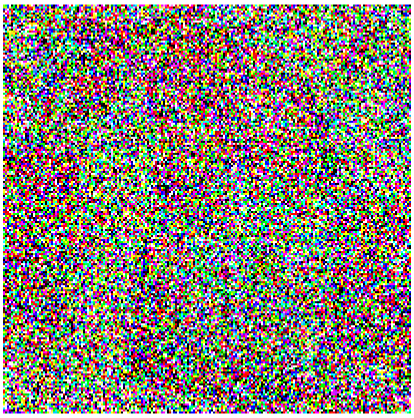
(a)

(b)

(c)

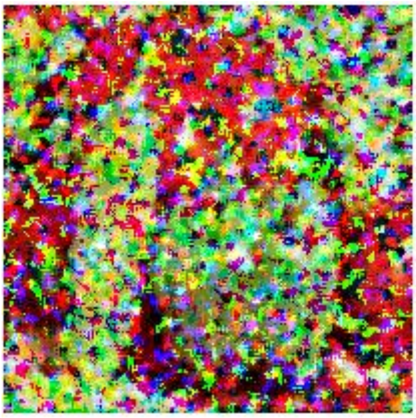
Fig. 1. Testing images we used.
(a) Peppers
(b) Baboon
(c) Lena

3. SIMULATION RESULTS



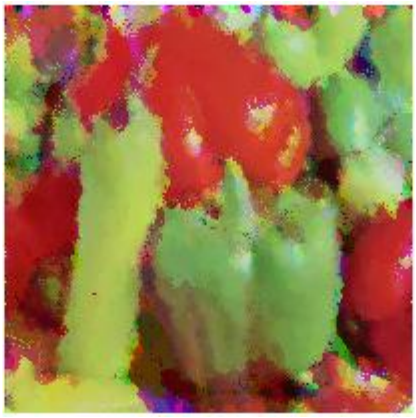
(a)

(b)



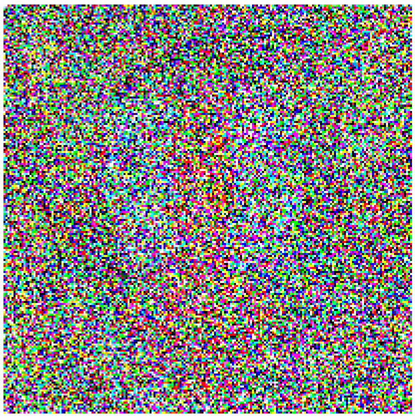
(c)

(d)



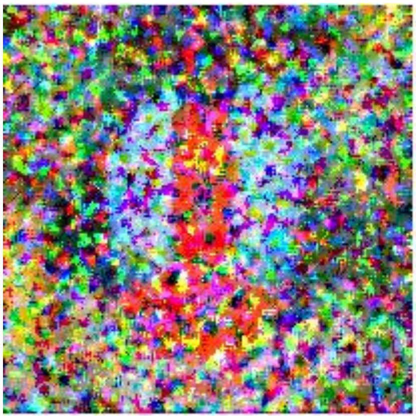
(e)

Fig. 2. Simulation Results of peppers corrupted with 80% impulse noise.
(a) Noisy image corrupted with 80% impulse noise
(b) Denoised image with BDND [8]
(c) Denoised image with Zhang SM filter [7]
(d) Denoised imaged with BDND2010[10]
(e) Denoised method with our proposed method



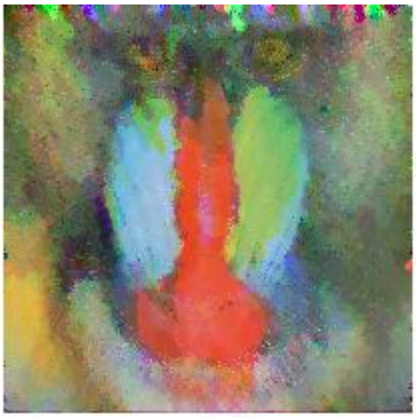
(a)

(b)



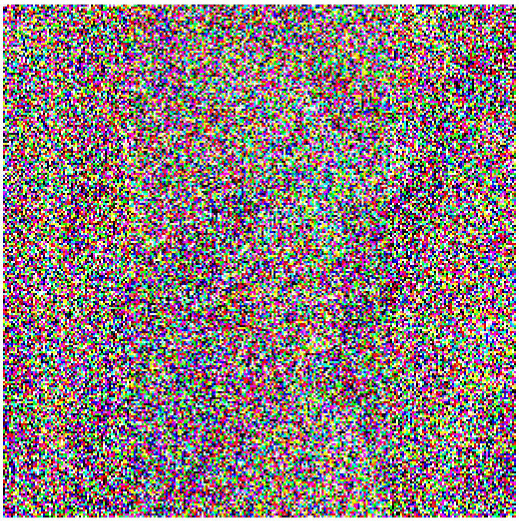
(c)

(d)



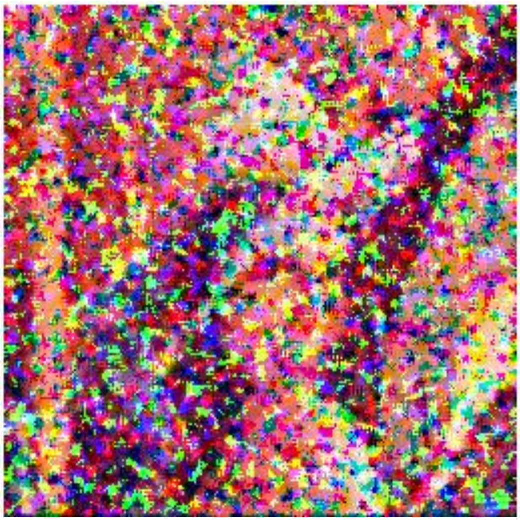
(e)

Fig. 3. Simulation Results of baboon corrupted with 80% impulse noise.
(a) Noisy image corrupted with 80% impulse noise
(b) Denoised image with BDND [8]
(c) Denoised image with Zhang SM filter [7]
(d) Denoised imaged with BDND2010 [10]
(e) Denoised image with our proposed method



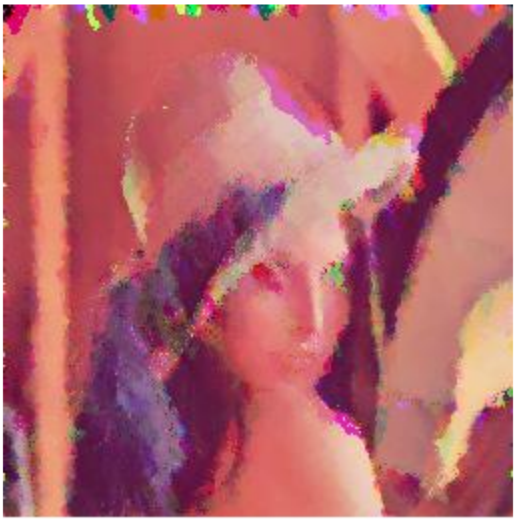
(a)

(b)



(c)

(d)



(e)

Fig. 4. Simulation Results of Lena corrupted with 80% impulse noise.
(a) Noisy image corrupted with 80% impulse noise
(b) Denoised image with BDND [8]
(c) Denoised image with Zhang SM filter [7]
(d) Denoised imaged with BDND2010 [10]
(e) Denoised image with our proposed method

TABLE : PSNR RATIO COMPARISON

	PSNR			
Noise %	**BDND**	**Zhang**	**BDND 2010**	**OURS**
10	33.03	26.55	32.56	34.36
20	30.88	26.25	30.61	31.29
30	28.82	25.27	28.84	28.9663
40	27.02	23.89	27.03	27.25
50	25.53	21.88	25.5	25.763
60	24.1	19.26	24.0	24.134
70	22.44	16.28	22.43	22.45
80	20.23	13.26	20.2	20.713

(a)

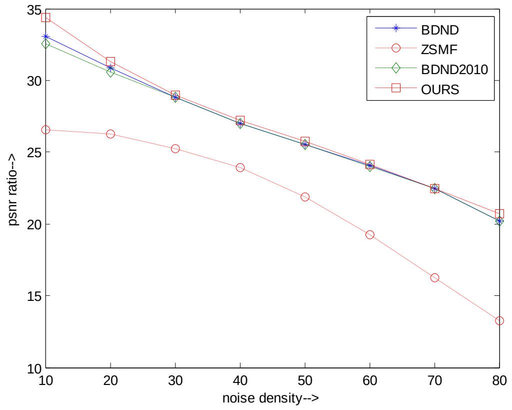
	PSNR			
Noise %	**BDND**	**Zhang**	**BDND 2010**	**OURS**
10	34.77	33.05	33.5	37.84
20	32.8	31.46	32.38	33.97
30	31.16	28.70	30.26	32.08
40	28.64	26.48	28.31	29.95
50	25.74	22.92	25.13	26.15
60	24.01	19.80	23.31	24.32
70	20.87	16.04	20.02	21.55
80	17.32	12.70	17.2	18.2

(b)

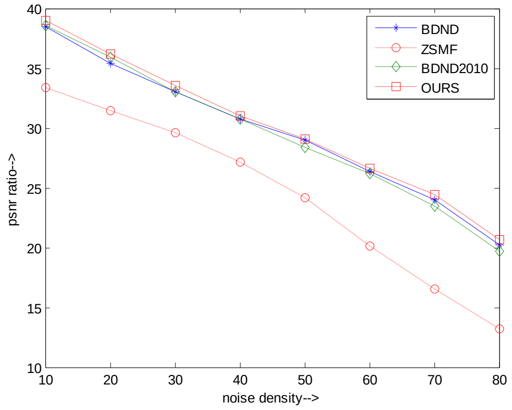
	PSNR			
Noise %	**BDND**	**Zhang**	**BDND 2010**	**OURS**
10	38.5	33.39	38.56	38.996
20	35.43	31.49	35.89	36.225
30	33.03	29.61	32.99	33.59
40	30.73	27.19	30.77	30.98
50	28.98	24.13	28.383	29.1
60	26.4	20.16	26.165	26.65
70	24.0	16.52	23.49	24.44
80	20.18	13.18	19.7	20.7

(c)

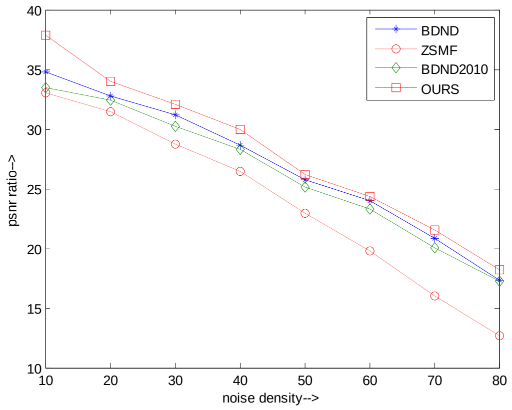
(a) Baboon image corrupted with 10-80% impulse noise denoised with BDND[8], Zhang[7], BDND2010[10], Proposed method
(b) Lena image corrupted with 10- 80% impulse noise denoised with BDND[8], Zhang[7], BDND2010[10], Proposed method
(c) Peppers image corrupted with 10-80% impulse noise denoised with BDND[8], Zhang[7], BDND2010[10], Proposed method



(a)



(b)



(c)

Fig. 5. (a)PSNR plot of denoised baboon image corrupted with 10-80% impulse noise
(b) PSNR plot of denoised Lena image corrupted with 10-80% impulse noise
(c) PSNR plot of denoised peppers image corrupted with 10-80% impulse noise

4. CONCLUSION

In this letter, we propose a simple and effective algorithm for removing high density impulse noise. The algorithm is fairly simple to understand and implement. The extensive simulation results done on the three images for various noise densities depict that our method achieves a better peak signal to noise ratio of the denoised image. Once the detection is done by our approach, a newly improved filtering technique can be used to further improve the results.

5. REFERENCES

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