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An Efficient Two-phase Method for Restoring Images Corrupted with Impulse Noise

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ABSTRACT

Impulse noise removal is considered as one of the most important pre-processing task in digital image processing (DIP). In literature there are two types of noise removal techniques called median filtering and weighted average filtering. But these suffer from either inefficient detection of corrupted pixels or low quality restoration. The present paper proposes a two-phased method viz. impulse detector and median filter (IDMF) which outperforms efficient weighted average (EWA) filter and fast and efficient median filter (FEMF) for a given set of test images which of grey scale and color images.

Keywords: Salt-and-pepper noise, image de-noising, Impulse detector and median filter

1. INTRODUCTION

Image gets affected with impulse noise because of many reasons, for instance defective memory locations in hardware or during acquisition and while data transmission[1]. When Salt-and-pepper noise is present in an image, the pixels in the image catch only the extreme values. As a consequence, white and black dot appears on images. For random-valued noise, corrupted pixels take any value within the range minimal to maximal value. This type of noise is little bit difficult to remove. So, there is a stringent requirement of a noise deduction method before any image processing operations [1]. Numerous methods are used to identify salt-and-pepper noise which first identifies the noisy pixels and then recover those leaving the uncorrupted pixels unaffected.

As an instance of Weighted-average filtering techniques we took Weighted Iterative Truncated Mean [WITM] filter [2], the cloud model (CM) filter [3] and efficient weighted average [EWA][4] filter but notices problems like inefficient restoration of corrupted pixels. Though, it was efficient in impulse noise detection.

Another method with a different approach for impulse noise removal is median filtering. And majority of the impulse noise exclusion methods are derived from median filtering. As an instance, Efficient Adaptive Weighted Switching Median Filter (EAWSM) [5], Adaptive Median filter (AMF) [6], Progressive Switching Median (PSM) filter [7] and Noise Adaptive Soft-Switching Median (NASM) filter [8].

As an instance of median filtering for removal of impulse noise we took the ease of fast and efficient median filter (FEMF), which replaces the noisy pixels with the median of surrounding pixels [9]. Although it was efficient in filtering but detection of corrupted pixels was not efficient which results in corruption of original background black and white pixels as well.

Since these two techniques viz. weighted average filtering and median filtering are thepredominantly used techniques. There is a constant necessity of a technique which is good fordetection as well as restoration. So, there is trade-off in these techniques.

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The present paper focuses on a technique which can provide information about the corrupted pixels to the greater level and then be able to restore them while leaving the original pixels remain unchanged. For detection of corruptedpixels, impulse detector is used [4] while the images are restored using fast and efficient median filter [9].

The remainder of this paper is organized as follows: impulse noise model is reviewed in Section 2. The intended method is presented in section 3. In section 4, experimental results and comparisons have been discussed and section V concludes this paper.

2. NOISE MODEL

Salt-and-Pepper Noise (SPN) is usually modeled by [1]

$$\tilde{x}_{i,j} = \begin{cases} N_{\min} \textit{ with probability } p1 \\ x_{i,j} \textit{ with probability } 1-p \\ N_{\max} \textit{ with probability } p2 \end{cases} \tag{1}$$

Where is original, $\tilde{x}$ is corrected pixel and is the amount of noise, correspondingly, and (i, j) is picture coordinate. In the model, it is shown that the pixels are arbitrarily ruined by two fixed extreme-grey values, N_{min} and N_{max}, with the same probability.

3. PROPOSED TWO-PHASE METHOD

Like other methods, for detection of salt-and-pepper (SPN) noise. This method also consist of two parts: impulse detector and image restoration

IMPULSE DETECTOR

On the way to categorize the affected pixels, first find the extreme grey level values. Though, marking all the pixels with 0 and 255 can fallout in false discovery of various noise-free pixels as noisy pixels. It is a fact that salt-and-pepper takes minimum and maximum values with same probabilities. Therefore, a strong inclination towards one of the impulse value in a neighborhood indicates that there are some uncorrupted pixels with an impulse value. Then, examine the inclination for each neighborhood and correlation of each doubtful or suspicious pixels with its surroundings to discriminate among the noisy and noise-free ones which include one of the extreme values. For strong inclination toward one impulse value, almost 75% of the neighbors in selected window of an image will be equal to one value of the impulse. The flow chart is shown in Fig. 1.

WINDOW SELECTION: Estimated noise probability and the probability of being uncorrupted is $\tilde{p}$ and $1-\tilde{p}$. Therefore, by the applying binomial distribution, the predictable noise-free pixel is $(w^2-1)(1-\tilde{p})$ inside a window dimension of $w \times w$. Trough simulations the optimal value of the uncorrupted pixels in the neighborhood of the pixel under consideration comes out to be 5. Because of which the window size is obtained as the smallest odd integer greater than $\sqrt{1+\frac{5}{1-p}}$..

It has been observed that lower number of uncorrupted pixel in the pixel's neighborhood increases the detection error and higher number results in bigger window which further affects the detection accuracy as the pixels involved have less correlation with the central pixel.

Step 1: The first footstep in the proposed 2-phase method is to determine the impulse values in image, N_{min} and N_{max} and then construct the set of doubtful pixels. For this reason, proposed method present a straight forward rule, mentioned in Eq. (2).

$$\Omega_I = \{(i, j) \mid \tilde{x}_{i,j} = N_{\min})(\tilde{x}_{i,j} = N_{\max})\} \tag{2}$$

Where symbol $\vee$ in (2) denotes logical OR. The set Ω_I contain the indices of doubtful or suspicious pixels.

Step 2: Calculate rate of suspicious pixels that is noise density and set window size up to the least odd integer more than $\sqrt{1+\frac{5}{1-p}}\cdot$.

Step 3: Now, compute pixel's count $d_{i,j}^{\min}$ and $d_{i,j}^{\max}$ within the neighborhood of the pixel on coordinate (i, j) through grey values up to N_{min} and N_{max}, correspondingly.

Step 4: Prepare datasets of uncorrupted pixels using N_{min}, N_{max}, w, $d_{i,j}^{\min}$ and $d_{i,j}^{\max}$, respectively. The datasets for this purpose are given below in Eq.(3) and Eq.(4).

$$\Omega_{D1} = \{(i, j \mid d_{i,j}^{\min} + d_{i,j}^{\max} = w^2)\} \tag{3}$$

$$\Omega_{D_2} = \left\{ \begin{array}{l} \left(i, j \,\middle|\, (\tilde{x}_{i,j} = N_{\min}) \left(d_{i,j}^{\max} < \dfrac{d_{i,j}^{\min}}{3} \right) \right) \\ \left((\tilde{x}_{i,j} = N_{\max}) \left(d_{i,j}^{\min} < \dfrac{d_{i,j}^{\min}}{3} \right) \right) \end{array} \right\} \tag{4}$$

symbol $\wedge$ is logical AND.

Where $\cap$ along with $\cup$ denotes the intersection and union operations and $\overline{A}$ meant for the complement set of A.

From equations (3)-(5) entail that the pixel by means of impulse value is regarded as noise-free if:

(1) Each and every one of its surrounding pixels contain values identical to the impulse values,

(2) The greater part of its surrounding pixels is liable to individual of the impulse values,

(3) It enriches in this inclination

Step 5: Prepare set of corrupted pixels from uncorrupted datasets.

$$\Omega = \Omega_I \cap \left(\overline{\Omega_{D1}} \cup \overline{\Omega_{D2}} \right) \tag{5}$$

Step 6: Set Mask matrix M for noisy image. Set 0 for noisy pixel and 1 for uncorrupted pixel in mask M.

$$M_{i,j} = \begin{cases} 0\, if\ (i, j) \in \Omega \\ 1\, if\ (i, j) \notin \Omega \end{cases} \tag{6}$$

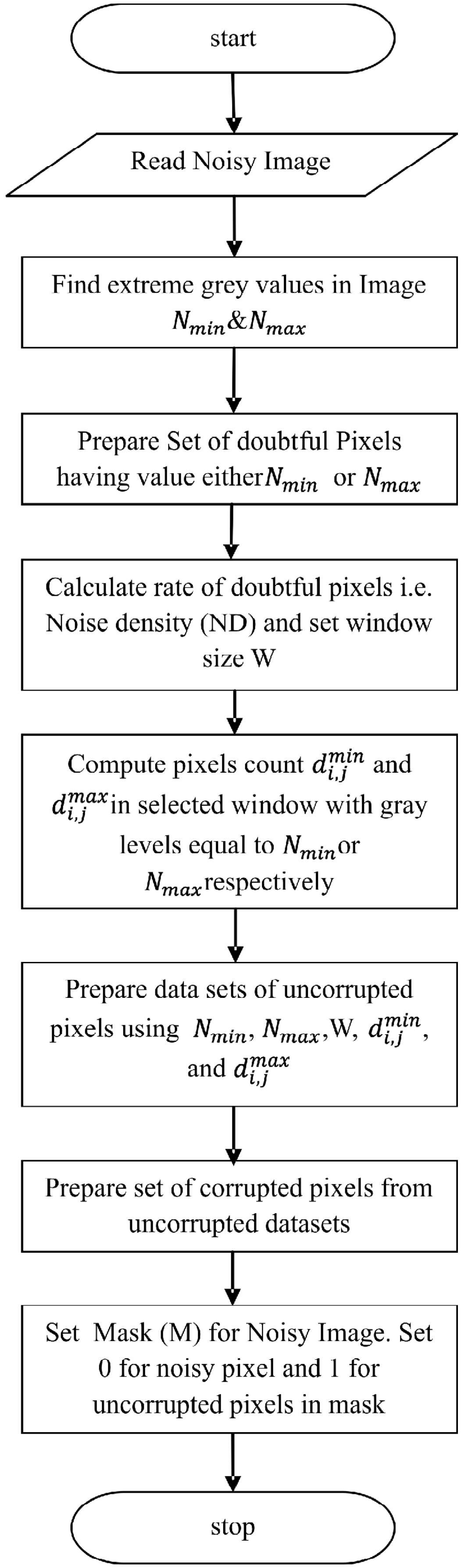

Figure 1: Flow chart of impulse detector

IMAGE RESTORATION

For image restoration, fast and efficient median filter (FEMF) is used. This filter can competently recover images degraded at 1 to 99% of noise ratio, by repairing only the noisy pixels through competent calculation. This is proficient with an adaptive median-filtering process to locate a best possible median for a particular corrupted pixel.

Different types of adaptive windows are engaged for various noise densities. To find the median, the surrounding pixel toward the middle corrupted pixel within a window is used to get the median between them. However, to take out the best median in a window depends upon the amount of neighbor pixels regarded as candidates. The first one window which is shown in Fig.2(a) is sufficiently used to find median of window which contain low noise density such as below 50% because noise free pixels be able to be simply searched for neighbors. Alternatively, a bigger window is designed for the noisy image at noise density higher than 50% because neighbors possibly will not contain suitable pixels toward every corrupted pixel. So, noise ratio will be calculated like the prior information toward the median filter.

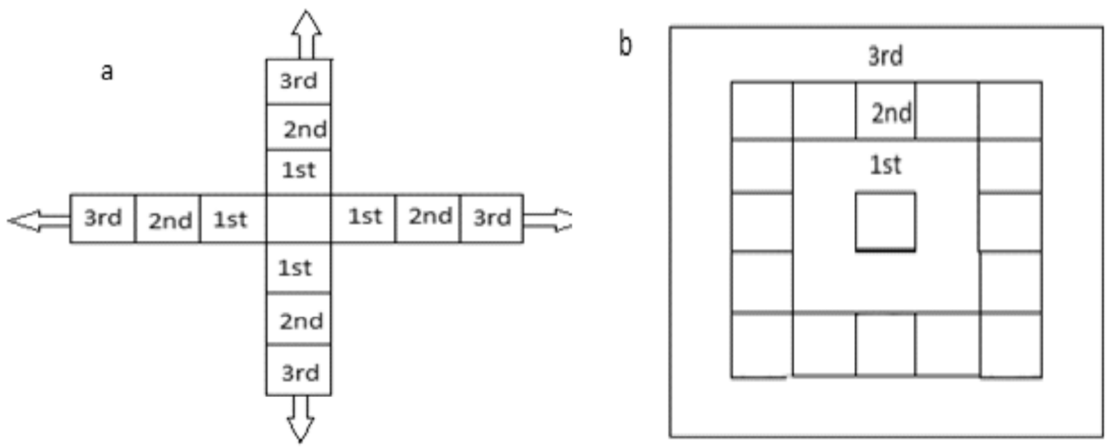

Figure 2: (a) Simplified window 3(b) Full window

The flow chart shown in Fig. 3 is given below in steps:

Step 1: In mask M, each and every pixel of it is checkered for the occurrence of salt-and pepper noise. If the mask M acquires salt-and-pepper noise like the dealing out pixel that is 0/255 pixel value, then window size is initialized to means 3 3 window size.else, the complete window have to be exist in use for the image at intensities higher than 50% on the way to find the remaining

Step 2: Now, if noise density is greater than 50% then choose complete window of size

$(2k + 1) \times (2k + 1)$. On the other, if noise density is less than 50% then select simplified window of size $(2k + 1) \times (2k + 1)$.

Step 3: If all pixels are corrupted in window, then increase the window size i.e. ? = ? + 1. The dimension of window is enlarged up to so as to ? < 6 find the uncorrupted pixels. Increasing the window dimension beyond ? > 6 will raise the computational difficulty of the proposed method. Now, if window does not include noise free pixels than select the different window size. If it includes noise free pixels then restore $(?, ?)_{?h}$ pixel with the average of window.

Step 4: Otherwise, if the entire pixels in window are not noisy than trim extreme values from the window. Then recover $(?, ?)_{?h}$ pixel with the median of residual elements. Hence, we get the de-noised image.

Step 5: If mask M contains all uncorrupted pixel, it does not need additional operations.

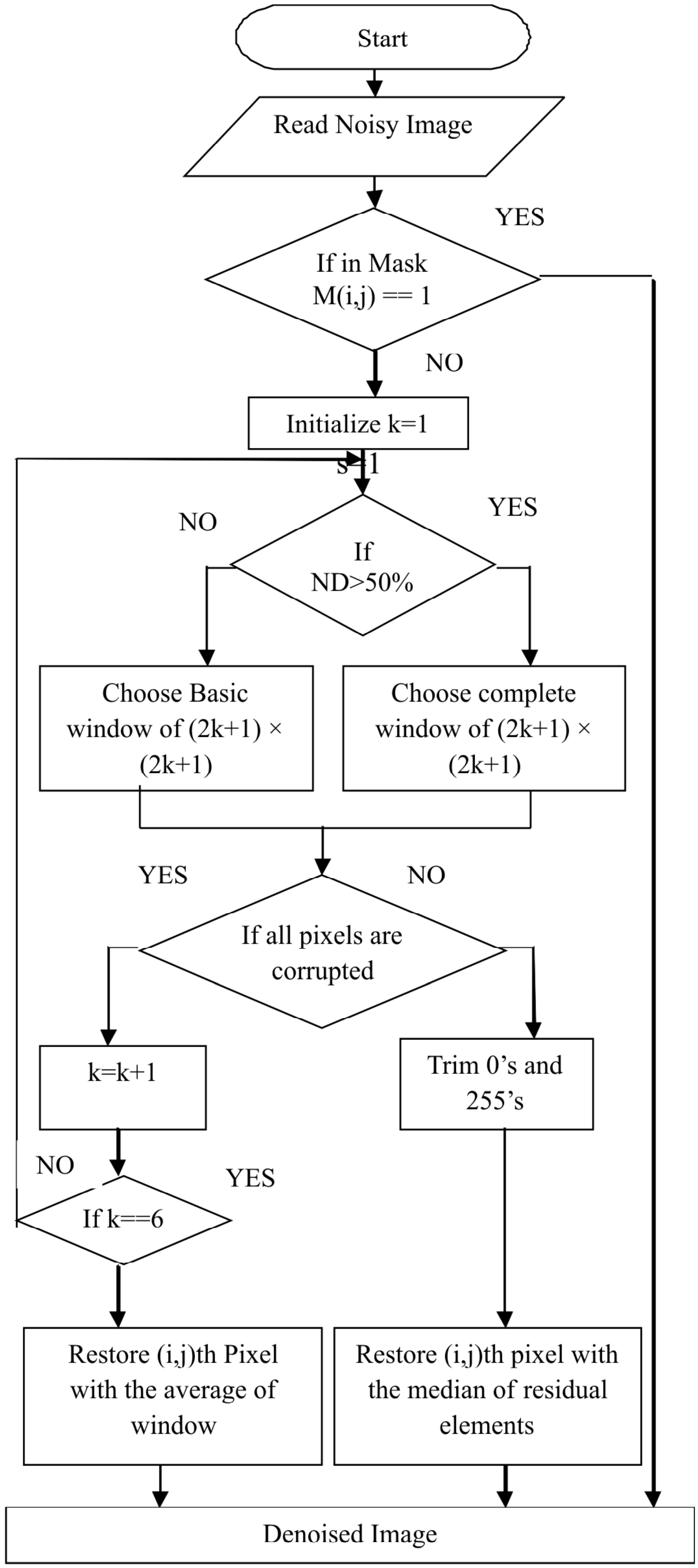

Figure 3: Flow chart of FEMF

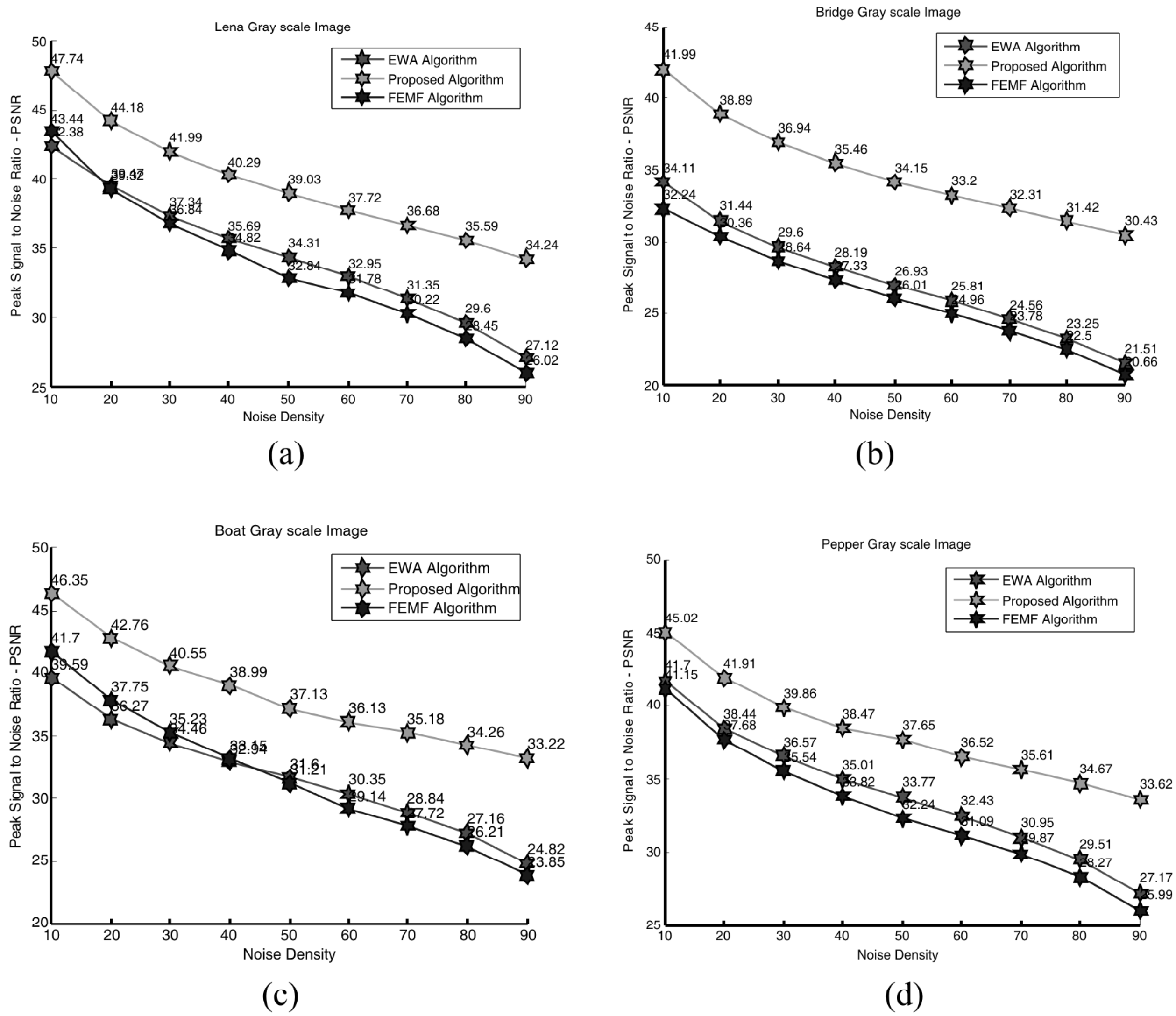

Figure 4: Comparison of restoration in terms of resultant PSNR for different grey-scale images corrupted by various densities of SPN. (a)Lena(b) Bridge (c) Boat (d)Pepper

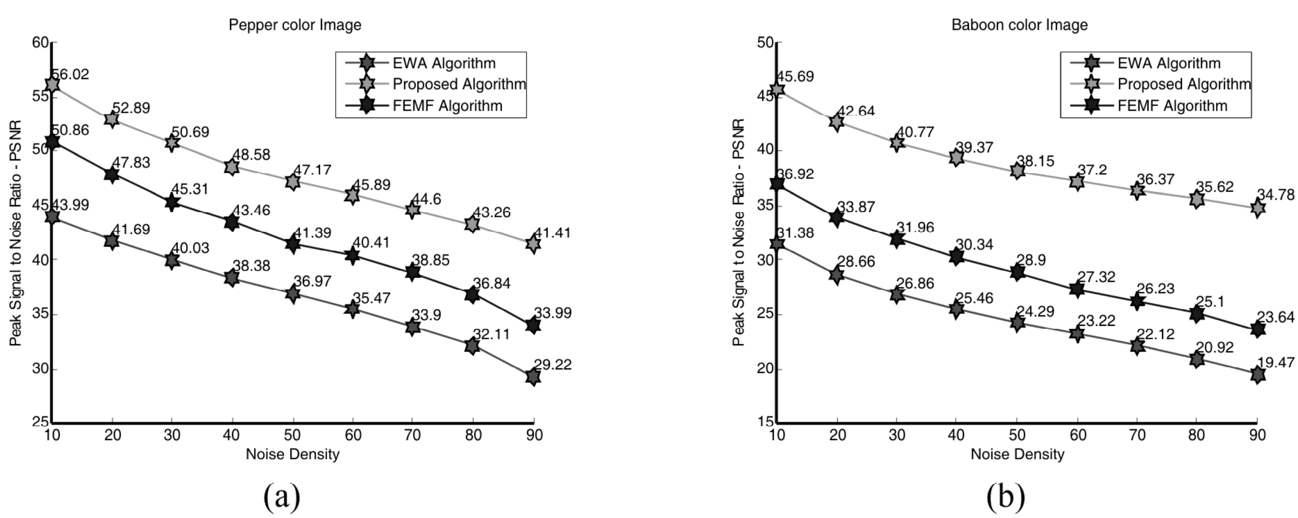

Figure 5: Comparison of restoration in terms of resultant PSNR for different color images corrupted by various densities of SPN. (a) Pepper (b) baboon

Table I
Results of MSE, PSNR, SSIM, IEF for Grey-scale Images Dealing With Several Noise Levels

Image	*Attribute*	*10*	*20*	*30*	*40*	*50*	*60*	*70*	*80*	*90*
Boat	MSE	1.506	3.44	5.723	8.197	12.58	15.84	19.7	24.33	30.93
	PSNR	46.35	42.76	40.55	38.99	37.13	36.13	35.18	34.26	33.22
	SSIM	0.997	0.994	0.99	0.984	0.969	0.956	0.937	0.904	0.827
	IEF	833.2	741.5	672.5	620.5	508.4	486.9	451.7	419	370.7
Lena	MSE	1.092	2.48	4.103	6.074	8.127	10.96	13.96	17.91	24.47
	PSNR	47.74	44.18	41.99	40.29	39.03	37.72	36.68	35.59	34.24
	SSIM	0.997	0.995	0.991	0.985	0.978	0.968	0.955	0.929	0.873
	IEF	1136	1023	928.2	839.9	783.5	699.4	639.3	569.5	468.1
Bridge	MSE	4.107	8.377	13.14	18.47	24.98	31.07	38.17	46.85	58.8
	PSNR	41.99	38.89	36.94	35.46	34.15	33.2	32.31	31.42	30.43
	SSIM	0.994	0.987	0.977	0.965	0.942	0.919	0.884	0.828	0.709
	IEF	306	304.1	288.7	272.8	253.4	245.1	232.3	216.1	193.6
Pepper	MSE	2.043	4.188	6.715	9.231	11.16	14.46	17.84	22.14	28.22
	PSNR	45.02	41.91	39.86	38.47	37.65	36.52	35.61	34.67	33.62
	SSIM	0.994	0.989	0.983	0.976	0.968	0.957	0.942	0.915	0.862
	IEF	617.6	601.2	571.7	552.5	571.6	529.7	499.9	461	405.6

Table II
Results of MSE, PSNR, SSIM, IEF for Color Images Dealing With Several Noise Levels

Image	*Attribute*	*10*	*20*	*30*	*40*	*50*	*60*	*70*	*80*	*90*
Baby	MSE	0.053	0.139	0.263	0.449	0.628	0.898	1.281	1.896	3.16
	PSNR	60.86	56.67	53.92	51.6	50.14	48.59	47.05	45.35	43.13
	SSIM	0.999	0.999	0.998	0.997	0.996	0.994	0.99	0.982	0.958
	IEF	806.4	610.2	485	378.2	337.3	293.4	231.2	179	120.6
Lena	MSE	0.962	1.103	1.749	2.527	3.292	4.25	5.435	6.9	9.026
	PSNR	51.17	47.7	45.7	44.1	42.95	41.84	40.77	39.74	38.57
	SSIM	0.996	0.991	0.985	0.978	0.969	0.957	0.939	0.91	0.849
	IEF	930.8	824.3	775.8	708.4	668.1	616.8	560.9	502.7	429.6
Baboon	MSE	1.752	3.536	5.439	7.504	9.954	12.37	14.99	17.82	21.61
	PSNR	45.69	42.64	40.77	39.37	38.15	37.2	36.37	35.62	34.78
	SSIM	0.991	0.981	0.966	0.947	0.915	0.879	0.835	0.766	0.638
	IEF	239.3	237.2	231.6	224	210.8	204.1	195.7	188.4	174.6
Pepper	MSE	0.162	0.333	0.553	0.901	1.246	1.671	2.254	3.063	4.698
	PSNR	56.02	52.89	50.69	48.58	47.17	45.89	44.6	43.26	41.41
	SSIM	0.998	0.998	0.996	0.978	0.99	0.986	0.979	0.964	0.926
	IEF	305.2	258.2	233.3	191.7	170.3	147.5	129.6	107.9	79.57

4. SIMULATION RESULTS

For simulation, four 512512 grey- scale test images *Lena*, *Boat*, *Bridge* and *Pepper* are taken. For simulation above mentioned algorithm is implemented on four grey-scale and three color images with varying noise density from 10%-90%. *Lena*, *Boat*, *Bridge* and *Pepper* of size 512512 are taken as grey-scale test images while *Baboon*, *Lena*, *Baby*and *Pepper* of size 512512 are taken as color test images. These images are tested against four parameters PSNR, MSE, SSIM and IEF.

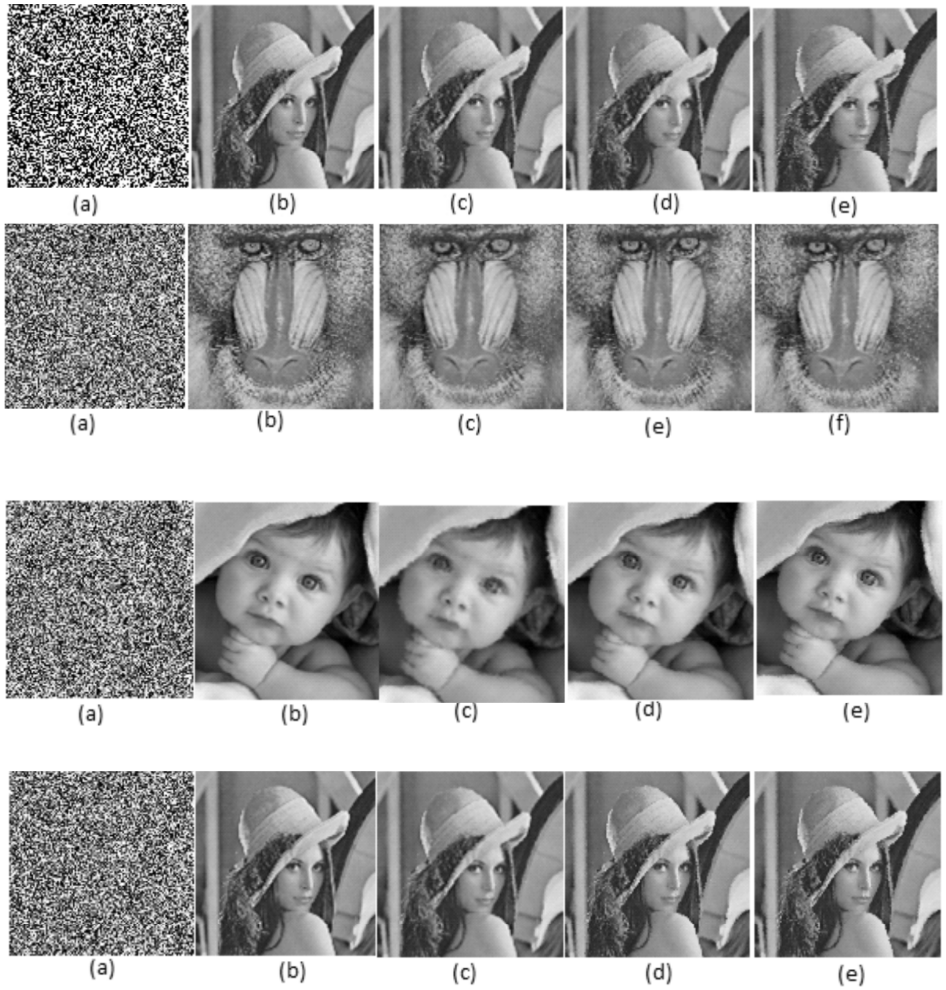

Figure 6: The results of image Lena (grey-scale), Baboon, Baby and Lena (color) corrupted by 90% SPN. (a) corrupted image (b) Original image (c) EWA (d) FEMF (e) IDMF

The implementation of the proposed algorithm for salt-and-pepper noise removal on test images with noise density of 10% and 90% have been shown in table I table II. Also, the case of grey-scale Lena of size 512512 with noise density 90% have been shown in figure 6(a) while figure 6(b) shows the original image and figures 6(c), (d) and (e) shows the results of employed EWA[4], FEMF[9] and IDMF respectively for visual comparisons. Similarly, results have been shown for Baboon, Baby and Lena color image.

More detailed results comparing the PSNR value of the restored image by employing EWA, FEMF and IDMF for varying noise density from 10% to 90% on test images have been shown graphically in figures 4 and 5. Clearly, the qualitative results show that the proposed method is very robust in impulse noise removal than the other methods. It can also be observed from the table that there is increase in PSNR value and decrease in MSE.

V. CONCLUSION

In this paper, trouble of image de-noising is considered and emphasis is given on a balanced impulse noise detection and image restoration process. It has been compared with EWA and FEMF techniques in terms of PSNR. Proposed method has been tested at low and high noise intensities going together grey scale as well as color images. Still at high intensity of noise the proposed technique outperforms other methods. Experimental results are also taken in terms of SSIM, IEF and MSE. Together visual and qualitative results are established.

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