A Novel Technique for Removal of Random Valued Impulse Noise Using All Neighbor Directional Weighted Pixels (ANDWP)

J.K. Mandal and Somnath Mukhopadhyay

Department of Computer Science and Engineering,
Kalyani University, Kalyani,
West Bengal, India, 741235
jkm.cse@gmail.com, som.cse@live.com
http://jkmandal.com, http://www.klyuniv.ac.in

Abstract. In this paper an All Neighbor Directional Weighted Pixels (ANDWP) based filter has been proposed for removal of highly random valued impulse noise (RVIN). The proposed approach works in two phases. The first phase detects the contaminated pixels by making the differences between the test pixel and its all neighbor pixels aligned in four main directions in the 5 x 5 window. The second phase filters only the noisy pixels based on minimum variance of the four directional pixels. Extensive simulations show that the proposed filter not only provide better performance of de noising RVIN but can preserve more fine detail features even thin lines.

Keywords: All neighbor directional weighted pixels, de noising, miss and false, random valued impulse noise, sensitivity, specificity.

1 Introduction

The nonlinear characteristics of noise affect the performance of linear filters. Median Filter is effectively used for such purposes[10]. The main drawback of the median filter is that it performs satisfactory for salt and pepper noise but not for images corrupted highly with RVIN and another thing is it also modifies the noise free pixels and blurs the images by removing the fine details. For performance enhancement, many filters with an impulse detector has been proposed, such as signal-dependent rank order mean (SD-ROM)[1] filter, adaptive center-weighted median (ACWM) [4] filter, (Med)[2] filter, multi state median (MSM)[5] filter and the pixel-wise MAD (PWMAD)[6] filter. These filters usually perform well but when the noise level is more than 30%, they do not give satisfactory performances even they cannot remove some black patches on the reconstructed images as well.

To deal with RVIN, a directional weighted median (DWM)[7] filter were proposed, which uses minimum of 8 to 10 iterations and a total of 16 neighbor pixels. The number of iterations used in detection and filtering of noisy image

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using median filter is very important, because not only it increases the complexity but also blurred the reconstructed image as the idea of applying the median filter recursively has been examined [10] and produced highly correlated image with increased blurring. The recent method of sa, dash and majhi[11] uses second order difference based noise suppression method, where all the neighborhood pixels in the 3 x 3 window are taken for such purpose. This method does not work well for highly corrupted images but it has very low computational cost.

The primary objective of the proposed work is to de noise the highly corrupted image as well as to preserve the quality of the reconstructed image. Proposed method uses all the neighborhood pixels for noise detection as well as for noise filtering in the 5 x 5 window.

The organization of the paper is as follows. Proposed impulse detector and filtering method are given in section 2 and 3 respectively. Experimental results and discussions are demonstrated in section 4. Conclusions are given in section 5.

2 Impulse Detector

There are two types of impulse noises; fixed and random valued impulses. In a gray scale image the fixed valued impulse, known as salt and pepper noise[9] occurs where pixel value converted to either 0 or 255 with equal probability, while the random valued impulses is uniformly distributed over the range of [0,255].

The proposed scheme applied on 5 x 5 window of the image in row major order to detect the noisy pixels, focuses on the pixels aligned in the four main directions along with two end pixels in each direction, shown in Fig 1. The proposed impulse detection is given in Algorithm 1.

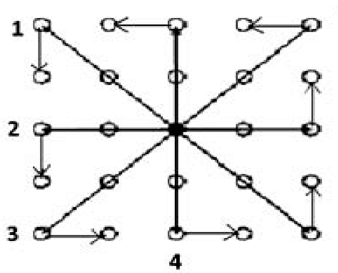

Fig. 1. Four Directional Weighted Pixels in the 5 x 5 Window

3 Impulse Filter

Most median based filters simply replace the noisy pixels by median values in the window. But when the objective is to de noise the images with highly random valued impulses, we cannot use conventional median filter because in that case most of the pixels were changed randomly in the noisy images. In this paper

Algorithm 1. Impulse detector

1: Let S_k (k=1 to 4) denotes a set of seven pixels aligned in the k^{th} direction centered at (0, 0), i.e.,
S_1 = {(-1,-2), (-2,-2), (-1,-1), (0, 0), (1, 1), (2, 2), (1, 2)}
S_2 = {(1,-2), (0,-2), (0,-1), (0, 0), (0, 1), (0, 2), (-1, 2)}
S_3 = {(2,-1), (2,-2), (1,-1), (0, 0), (-1, 1), (-2, 2), (-2, 1)}
S_4 = {(-2,-1), (-2, 0), (-1, 0), (0, 0), (1, 0), (2, 0), (2,1)}.
Then let $S_k^0 = S_k/(0,0)$, $\forall$ k =1 to 4.

2: In each direction of the 5 x 5 window centered at (i,j), define $d_{i,j}^{(k)}$ as the sum of all absolute differences of gray values between $y_{i+s,j+t}$ and $y_{i,j}$ with (s,t)$\in S_k^0$ (k= 1 to 4), given in eqn. 1.

3: In each direction, weigh the absolute differences between two closest pixels from the center pixel with a large ω_m, weigh the the absolute differences between the center pixel and the corner pixels by ω_n and that of absolute differences between two end pixels from the center pixel with a small ω_o. Assign ω_m =2, ω_n=1 and ω_o=0.5.
Thus define

$$d_{i,j}^{(k)} = (\sum_{(s,t)\in S_k^0} \omega_{s,t}|y_{i+s,j+t} - y_{i,j}|, 1 \le k \le 4) \tag{1}$$

where

$$\omega_{s,t} = \begin{cases} \omega_m & : (s,t) \in \Omega^3 \\ \omega_o & : (s,t) \in \Omega^2 \\ \omega_n & : \text{otherwise} \end{cases} \tag{2}$$

where

$$\Omega^3 = \{(s,t) : -1 \le s,t \le 1\}, and \tag{3}$$

where

$$\Omega^2 = \{(s,t) : (s,t) = \pm\{(-2,-1),(-1,-2),(1,-2),(2,-1)\}\}. \tag{4}$$

4: $d_{i,j}^{(K)}$ is termed as direction index. The minimum of these four direction indices are used for impulse detection, which is denoted as

$$r_{i,j} = min\{d_{i,j}^{(k)} : 1 \le k \le 4\} \tag{5}$$

Three assumptions may be made depending on the values of $r_{i,j}$.

1. $r_{i,j}$ is small when the current pixel is on a noise free flat region.
2. $r_{i,j}$ is small when the current pixel is on the edge.
3. $r_{i,j}$ is large when the current pixel is noisy .

5: From the definition of $r_{i,j}$, a noisy pixel is identified efficiently from the window of noise free pixels by employing a threshold(T).
Define the impulse detector as

$$y_{i,j} = \begin{cases} NoisyPixel & : r_{i,j} > T \\ NoiseFreePixel & : r_{i,j} \le T \end{cases} \tag{6}$$

a new scheme has been introduced based on minimum variance of all the four directional pixels. Starting with a noisy image and a threshold value (T), in row major order it scans each 5 x 5 window in the noisy image. If any pixel is detected as noisy, the filtering scheme restores it to a pixel which is most suitable in the 5 x 5 window. The technique has been depicted in algorithm 2.

Algorithm 2. Impulse filter

1: Calculate the standard deviations $\sigma_{i,j}^{(k)}$ of gray values of all $y_{i+s,j+t}$ with (s,t) $\in S_k^0$ (k= 1 to 4).

2: Find the minimum of $\sigma_{i,j}^{(k)}$, where k= 1 to 4, as

$$l_{i,j} = \min_k \{\sigma_{i,j}^{(k)} : k = 1 \ to \ 4\} \tag{7}$$

3: Select the set of seven pixels in the $l_{i,j}$ direction.

4: Replace the middle pixel of the set of pixels by a variable x to construct the set given in eqn. 8).

$$S = \{a, b, c, x, d, e, f\}. \tag{8}$$

5: Form a quadratic equation f(x) by calculating the variance (σ^2) of the step 4, as given in eqn. 9.

$$\begin{aligned} f(x) = (a - mean)^2 + (b - mean)^2 + (c - mean)^2 \\ + (x - mean)^2 + (d - mean)^2 + (e - mean)^2 + (f - mean)^2 \end{aligned} \tag{9}$$

where

$$mean \ = (a + b + c + x + d + e + f)/7. \tag{10}$$

6: Compute first order and second order derivatives (f' (x)) and (f''(x)) respectively of f(x).

7: f''(x) is always positive for any value of x, where x $\in$ [0, 255]. So by solving the equation f'(x) =0, get an x, where x $\in$ [0,255], for which f(x) is minimum.

8: Replace $y_{i,j}$ by x.

Methods of detection and filtering of noisy pixels work with three important user parameters, viz., Number of Iterations (I), Threshold Value (T) and Decreasing Rate(R) of Threshold Value in each iteration. These parameters are tuned to obtain much better results and described in Section 4.4.

4 Results and Discussions

Experiment has been performed on various benchmark images and comparisons are made with various available algorithms. Image restoration results are quantitatively measured in terms of Mean Squared Error(MSE), Peak Signal to Noise

Ratio(PSNR) and Image Fidelity(IF). So we give all results in terms of these three parameters.

4.1 Results

Table 1 gives the restoration results in terms of MSE and IF on three bench mark images for 50% and 60% corrupted images. It is seen from these results that the proposed ANDWP filter performs very good in objective(MSE) evaluation and also preserves the fidelity of the enhanced image.

Table 1. Restoration Results for *Lena*, *Boat* and *Bridge* images using ANDWP Filter

Filter	*Lena*		*Boat*		*Bridge*	
	50%	60%	50%	60%	50%	60%
MSE	57.94	96.29	87.27	131.21	182.79	269.61
IF	0.996699	0.994514	0.995407	0.993095	0.988573	0.983093

4.2 Comparisons

To evaluate the performance of the proposed algorithm with the existing algorithms, proposed filter has been compared with various existing techniques and the results of comparison on 512 x 512 *Lena* image corrupted with various degree of noises are given Table 2. It is seen from this table that the performances of the MED[3] operator is very poor. PSM[12] is much better than the MED[3] in restoring only 20% corrupted images. Performance of ACWM[4], MSM[5], SD-ROM[1] and Iterative Median[8] are almost similar. Among them, SD-ROM[1] performs best in restoring 40% to 60% noise densities. PWMAD[6] performs better than the second order[11] filter in all cases except 60% case. DWM[7] operator outperforms than any existing filter in all cases. But the proposed filter performs significantly better than any existing filter in restoring 40% or more corrupted images.

On close observation of table 3 and table 4 it is seen that for *Bridge* and *Boat* images DWM[7] filter performs better than any existing filters in terms *PSNR(dB)*. But ANDWP performs better than any existing filter in restoring 40% or more corrupted images.

Fig. 2 shows the comparative results of restoration between the existing filters and ANDWP on 60% noisy *Lena* image. It is seen from the figure that the output image using MSM[5] contains maximum noisy patches and performs worst. SD-ROM[1] and PWMAD[6] performs better than MSM[5] but not so good as it contains noises in the reconstructed image. Though DWM[7] performs satisfactory as it removes the impulses but still can not remove some black patches on the enhanced image. From the figure it is clear that the ANDWP obtains best restoration results. Considering very high noise density and fine details of the images, the performance of the proposed filter is very good.

Table 2. Comparison of restoration results in terms of PSNR for *Lena* Image

Filter	20% Noisy	30% Noisy	40% Noisy	50% Noisy	60% Noisy
Med[3]	30.37	30	27.64	24.28	21.58
PSM[12]	35.09	30.85	28.92	26.12	22.06
ACWM[4]	36.07	32.59	28.79	25.19	21.19
MSM[5]	35.44	31.67	29.26	26.11	22.14
SD-ROM[1]	35.72	30.77	29.85	26.80	23.41
Iterative Median[8]	36.90	31.76	30.25	24.76	22.96
2nd Order[11]	34.35	32.53	30.90	28.22	24.84
PWMAD[6]	36.50	33.44	31.41	28.50	24.30
DWM Filter[7]	37.15	34.87	32.62	30.26	26.74
ANDWP	34.42	33.01	32.65	30.50	28.29

Table 3. Comparison of restoration results in terms of PSNR (dB) for *Bridge* image

Filter	40% Noisy	50% Noisy	60% Noisy
ACWM[4]	23.23	21.32	19.17
MSM[5]	23.55	22.03	20.07
SD-ROM[1]	23.80	22.42	20.66
2nd Order[11]	23.73	22.14	20.04
PWMAD[6]	23.83	22.20	20.83
DWM Filter[7]	24.28	23..04	21.56
ANDWP	26.38	25.51	23.42

Table 4. Comparison of restoration results in terms of PSNR (dB) for *Boat* image

Filter	40% Noisy	50% Noisy	60% Noisy
ACWM[4]	26.17	23.92	21.37
MSM[5]	25.56	24.27	22.21
SD-ROM[1]	26.45	24.83	22.59
PWMAD[6]	26.56	24.85	22.32
DWM Filter[7]	27.03	25.75	24.01
ANDWP	29.23	28.72	26.95

4.3 Comparison of *Sensitivity* and *Specificity* Values

Prior to applying the filtering operator on any corrupted image, noise detection is very important. Number of noisy pixels those are not identified by the process is known as *miss* value and number of noise free pixels those are identified as noisy pixels by the technique is known as *false* value. Both of these values are required to be minimized.

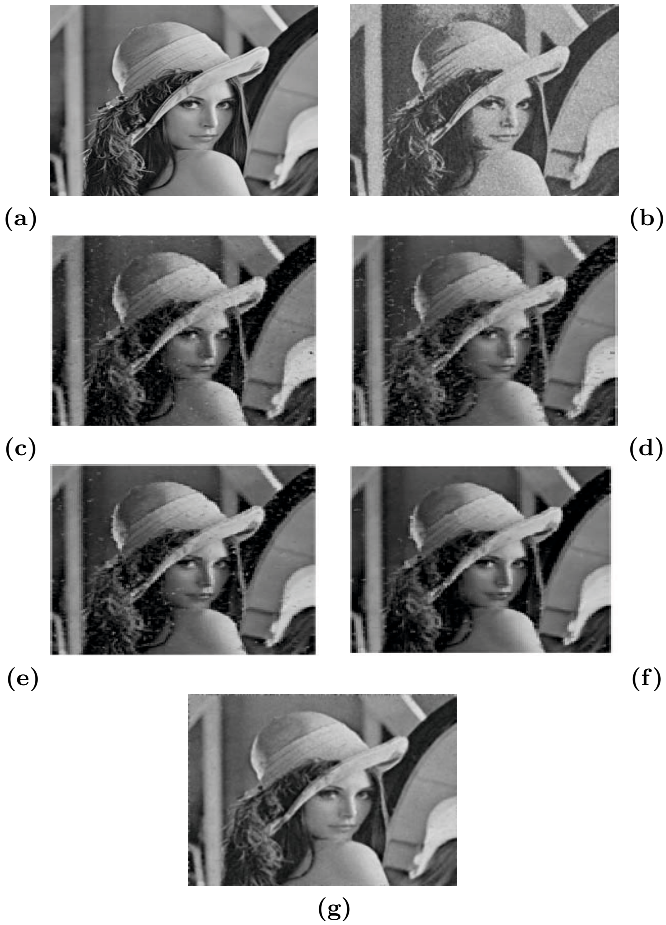

Fig. 2. Results of different filters in restoring 60% corrupted image Lena, (a) Original image (b)Noisy Image (c) (SD-ROM)[1] (d)(MSM)[5] (e)(PWMAD)[6] (f)(DWM)[7] (g)Proposed Filter

From table 5 it is seen that SD-ROM[1] and ACWM[4] filter give very good *false* values when it applied on 40% corrupted *lena* image but it performs very poor to identify the noisy pixels and generate noticeable patches on the reconstructed image. But ANDWP filter can identify the noisy pixels as well as it can ignore the noise free pixels with a remarkable difference compared to all other existing filters, by obtaining optimal *miss* and *false* values.

Two other statistical performance evaluation tools of noise detection algorithm are sensitivity and specificity. Sensitivity measures the percentage of noisy pixels which are correctly identified as having the condition. Specificity measures the percentage of noise free pixels which are correctly identified as not having the condition.

Table 5. Comparison of *miss* and *false* Results for *Lena* image

Filter	40% Noisy		50% Noisy		60% Noisy	
	Miss	False	Miss	False	Miss	False
SDROM[1]	22842	411	32566	998	45365	2651
MSM[5]	16582	7258	20857	10288	26169	15778
ACWM[4]	16052	1759	23683	2895	32712	7644
PWMAD[6]	11817	9928	14490	15003	17760	19577
DWM[7]	9512	7761	9514	11373	12676	12351
ANDWP	7852	6018	8260	7512	8812	9304

Table 6. Comparison of *Sensitivity* and *Specificity* Results for *Lena* image

Filter	40% Noisy		50% Noisy		60% Noisy	
	Sensitivity	Specificity	Sensitivity	Specificity	Sensitivity	Specificity
SDROM[1]	78%	99%	72%	99%	71%	98%
MSM[5]	84%	97%	84%	92%	83%	89%
ACWM[4]	84%	98%	81%	97%	79%	95%
PWMAD[6]	88%	90%	88%	88%	88%	87%
DWM[7]	90%	92%	92%	91%	91%	92%
ANDWP	93%	94%	94%	94%	94%	94%

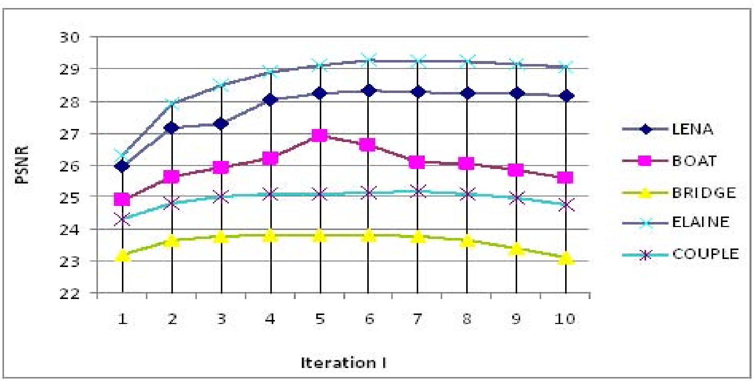

Fig. 3. Comparison of *PSNR* against *iteration* on various benchmark images

Sensitivity and specificity obtains from various filters for for 40% to 60% noisy *Lena* images are given in table 6. Proposed ANDWP performs better than any existing filters as it is most sensitive to detect true positives and also most specific to detect the true negatives.

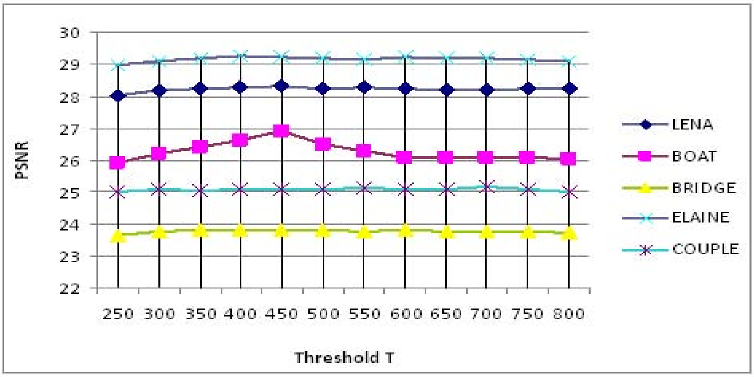

Fig. 4. Comparison of *PSNR* against *threshold* on various benchmark images

4.4 Threshold Value (T), no. of Iterations (I) and Decreasing Rate(R) of Threshold Value in Each Iteration

In this paper, the proposed scheme uses three user parameters viz., I, T and R in the following ranges to show the contributions of these three parameters. These are maximum number of iterations(I)$\in$ [5, 6], threshold value(T) $\in$ [300, 500] and decreasing rate of threshold value in each iteration (R) $\in$ [0.7, 0.9].

From fig. 3 and 4, we can see the restoration results using the proposed filter in terms of PSNR(dB) for 60% corrupted five bench mark images for the various ranges of values of the three parameters. Fig. 3 gives the relationship of PSNR against I and that of fig. 4 gives the correspondence of PSNR against T. In these two charts, the maximum PSNR values are plotted. In fig. 3, the PSNR at I=5 is obtained by varying T from 250 to 800 with an increment of 50 and R from 0.7 to 0.9 with an increment of 0.05 (I=5, T $\in$ [250, 800], R $\in$ [0.7, 0.9]) and then the maximum PSNR is plotted in the chart. In the same way in fig. 4, the PSNR at T=500 is obtained by varying I from 1 to 10 with an increment of 1 and R from of 0.7 to 0.9 with an increment 0.05 (T=500, I $\in$ [1, 10], R $\in$ [0.7, 0.9]) and then the maximum PSNR is plotted in the chart.

From these two figures it is seen that, by varying the parameters in a wide range we can obtain optimal restoration results for different images.

5 Conclusion

In this paper, a variance based filter has been proposed for removing high random valued impulse noise from digital images. In the proposed algorithm, all the 24 neighbors of the center pixel in the 5 x 5 window are included and used for noise detection. As a result it gives very less miss and false values compared to other filters. It obtains best sensitivity and specificity results too. The fundamental superiority of the proposed operator over most other operators is that it efficiently removes impulse noises from highly corrupted images while successfully preserves the thin lines, edges and fine details in the enhanced image.

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