A MODIFIED DIRECTIONAL WEIGHTED CASCADED-MASK MEDIAN FILTER FOR REMOVAL OF RANDOM IMPULSE NOISE

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ABSTRACT

In this paper a Modified Directional Weighted Cascaded-Mask Median (MDWCMM) filter has been proposed, which is based on three different sized cascaded filtering windows. The differences between the current pixel and its neighbors aligned with four main directions. A direction index is used for each edge aligned with a given direction. Then, the minimum of these four direction indexes is used for impulse detection for each and every masking window. Depending on the minimum direction indexes among the three windows one window is selected. The filtering is done on this selected window. Extensive simulations showed that the MDWCMM filter provides good performances of suppressing impulse with low noise level as well as for highly corrupted images from both gray level and colored benchmarked images.

KEYWORDS

Modified Directional Weighted Cascaded-Mask Median filter (MDWCMMF, PSNR, SNR, Median, gray & color image.

1. INTRODUCTION

Impulse noise is often introduced into images during acquisition and transmission [12,13]. Based on the noise values, it can be classified as the easier-to-restore salt-and-pepper noise and the more difficult random-valued impulse noise [9]. Among all kinds of methods for impulse noise, the median filter [10,11] is used widely because of its effective noise suppression capability and high computational efficiency [7]. However, it uniformly replaces the gray-level value of every pixel by the median of its neighbors. Consequently, some desirable details are also removed, especially when the window size is large. In order to improve the median filter, many filters with an impulse detector are proposed. In this paper a modified filter is used for removal of random-valued impulse noise which performs well in restoration of both low and high valued random impulse noise from both the gray and color images.

In an image, distinct gray levels are to be like their neighbors. So if a pixel value got corrupted, then considering its neighboring gray values we can restore the actual value. This filter

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(MDWCMMF) replaces the value of a pixel by the median of gray levels of neighborhood pixels of that pixel with a certain weight (1 or 2) and the pixels in the minimum weighted direction. The minimum weighted direction is one of the four directions (as shown in Figure.1) in which the sum of absolute differences of gray level values between the pivot(central) pixel value and its neighboring pixel values is minimum.

RGB color space is used as the basic color space for the color images. In RGB model colors are represented as a 3-D vector, with red as first element, green as second and blue as third element.

The organization of this paper is as follows. The new impulse detector is formulated in section 2. Section 3 described the filtering framework. Section 4 provides a number of experimental results to demonstrate the performance of the proposed MDWCMM filter. Conclusions are drawn in section 5.

2. IMPULSE DETECTOR

A noise-free image consists of locally smoothly varying areas separated by edges. Here, we only focused on the edges aligned with four main directions as shown in Figure 1.

Let $S_k^{(7)}$(k=1 to 4) denote a set of coordinates aligned with the kth direction centered at (0,0), taking (7×7) window, i.e.,

S_1={(-3,-3),(-2,-2), (-1,-1), (0,0), (1,1), (2,2),(3,3)}
S_2={(0,-3),(0,-2), (0,-1), (0,0), (0,1), (0,2),(0,3)}
S_3={(3,-3),(2,-2),(1,-1),(0,0), (-1,1), (-2,2),(-3,3)}
S_4={(-3,0),(-2,0), (-1,0), (0,0), (1,0), (2,0),(3,0)} (1)

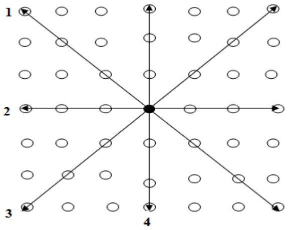


Figure 1: Alignment of edges in four directions

Let $S_k^{(5)}$ (k=1 to 4) denote a set of coordinates aligned with the kth direction centered at (0,0), taking (5×5) window, i.e.,

S_1={(-2,-2), (-1,-1), (0,0), (1,1), (2,2)}
S_2={(0,-2), (0,-1), (0,0), (0,1), (0,2)}
S_3={(2,-2),(1,-1),(0,0), (-1,1), (-2,2)}
S_4={(-2,0), (-1,0), (0,0), (1,0), (2,0)} (2)

Let $S_k^{(3)}$ (k=1 to 4) denote a set of coordinates aligned with the kth direction centered at (0,0), taking (3×3) window, i.e.,

S_1={(-1,-1), (0,0), (1,1)}
S_2={(0,-1), (0,0), (0,1)}
S_3={(1,-1),(0,0), (-1,1)}
S_4={(-1,0), (0,0), (1,0)} (3)

Now in a 7×7 window centered at (i, j), for each direction, define $d_{i,j}^{(p)(k)}$ as the sum of all weighted absolute differences of gray-level values between $y_{i+s,\,j+t}$ and $y_{i,\,j}$ with $(s,t) \in S_k^{(p)}$ for all k from 1 to 4, p={7,5,3}. Considering that for two pixels whose spatial distance is small, their grey-level values should be close to each other, we will weight the absolute differences between the two closest pixels with a larger value $w_{s,t}$ is very large, it will cause that $d_{i,j}^{(p)(k)}$ is mainly decided by the differences corresponding to $w_{s,t}$. Thus we have eq.4,

$$d_{i,\,j}^{(p)(k)} = \sum_{(s,\,t)} w_{s,t} * \mid y_{i+s,\,j+t} - y_{i,\,j} \mid ,\ 1 \le k \le 4,\ (s,t) \in S_k^{(p)} \tag{4}$$

Where

$$w_{s,t} = \begin{cases} 2, & (s,t) \in \Omega^3 \\ 1, & \text{otherwise} \end{cases}$$

$\Omega^3 = \{(s, t) : -1 \le s, t \le 1\}$,
P={3,5,7}.

Here, $d_{i,\,j}^{(p)(k)}$ are the direction indexes. Each direction index is sensitive to the edge aligned with a given direction. Then, the minimum of these four direction indexes is used for impulse detection, which can be denoted as in eq. 5.

$$r_{i,j}^{(p)} = \min \{ d_{i,\,j}^{(p)(k)} : 1 \le k \le 4, p=\{3,5,7\}\}, \tag{5}$$

We can find that by employing a threshold T_p, (p={3,5,7}), we can identify the impulse in each window from the noise-free pixels, no matter which are in a flat region, edge or thin line. Then, the pixel $y_{i,\,j}$ will be noisy if at least one of the following conditions holds

- $r_{i,j}^{(7)} > T_7$
- $r_{i,j}^{(5)} > T_5$
- $r_{i,j}^{(3)} > T_3$

The pixel $y_{i,\,j}$ will be noise free otherwise.

3. FILTER

After impulse detection, we replace the noisy pixels by the calculated median values of the window depending upon the four directions. For this first calculated the standard deviation $\sigma_{i,j}^{(p)(k)}$ of grey-level values for all $y_{i+s,j+t}$ with $(s,t) \in S_k^{(p)}$ (k= 1 to 4), {p=7,5,3}, respectively. Let take eq.6 as under

$$L_{i,j}^{(p)} = \min \{ \sigma_{i,j}^{(p)(k)} : k= 1 \text{ to } 4, p=\{3,5,7\} \} \tag{6}$$

Since the standard deviation describes how tightly all the values are clustered around the mean in the set of pixels, $L_{i,j}^{(p)}$ shows the pixels aligned with this direction are the closest to each other. Therefore the center value should also be close to them in order to keep the edges intact.

Three median values are calculated using the eq.7 as below

$m_{i,j}^{(7)} = \text{median} \{ w * y_{i+s,\,j+t} , y_{i+p1,\,j+q} : (s,t) ,(p1,q) \in S_k^{(7)}\}$

$m_{i,j}^{(5)} = \text{median} \{ w * y_{i+s,\,j+t} , y_{i+p1,\,j+q} : (s,t) ,(p1,q) \in S_k^{(5)}\}$

$m_{i,j}^{(3)} = \text{median} \{ w * y_{i+s,\, j+t} ,\, y_{i+p1,\, j+q} : (s,t) ,(p1,q) \in S_k^{(3)} \}$

where

$$w = \begin{cases} 2, & \text{if } -1 \leq (s,t) \leq 1 \\ 1, & \text{otherwise} \end{cases}$$

(s, t) pixels are on the minimum direction
And
$-1 \leq (p1,q) \leq 1$; where $(p1, q) \neq (s,t)$. (7)

Now, we can give the output of the proposed filter as in eq.8.

$$u_{i,j} = \begin{cases} u1, & \text{if } L_{i,j}^{(7)} = L_{i,j}^{(5)} \\ u1, & \text{if } L_{i,j}^{(7)} = L_{i,j}^{(3)} \\ u2, & \text{if } L_{i,j}^{(3)} = L_{i,j}^{(5)} \\ (u1+u2+u3)/3, & \text{otherwise} \end{cases} \tag{8}$$

$u1=\alpha_{i,j} * y_{i,j} + (1 - \alpha_{i,j}) * m_{i,j}^{(7)}$
where,

$$\alpha_{i,j} = \begin{cases} 0, & \text{if } r_{i,j}^{(7)} > T_7 \\ 1, & \text{if } r_{i,j}^{(7)} \leq T_7 \end{cases}$$

$u2=\alpha_{i,j} * y_{i,j} + (1 - \alpha_{i,j}) * m_{i,j}^{(5)}$
where,

$$\alpha_{i,j} = \begin{cases} 0, & \text{if } r_{i,j}^{(5)} > T_5 \\ 1, & \text{if } r_{i,j}^{(5)} \leq T_5 \end{cases}$$

$u3=\alpha_{i,j} * y_{i,j} + (1 - \alpha_{i,j}) * m_{i,j}^{(3)}$
where,

$$\alpha_{i,j} = \begin{cases} 0, & \text{if } r_{i,j}^{(3)} > T_3 \\ 1, & \text{if } r_{i,j}^{(3)} \leq T_3 \end{cases}$$

Then substitute

$$y_{i,j} = u_{i,j}$$

$$T = \begin{cases} T_3, & \text{for } (3 \times 3) \text{ window} \\ T_5, & \text{for } (5 \times 5) \text{ window} \\ T_7, & \text{for } (7 \times 7) \text{ window} \end{cases}$$

Iteration has been started with the value of T=510 (twice the maximum of gray value). At T=510, the PSNR for the restored image of the 40% noisy Lenna image(Figure 2.e) was 17.01 dB; but if in the filtering eq.8. was applied recursively and iteratively with decreasing threshold (T=T*0.8), the PSNR for the restored images of the 40% noisy Lenna image has been increased as shown in the table 1.

Table 1: PSNR for the restored images of "Lenna" based on changing thresholds, corrupted by 40% of Random-valued impulse noise

Value of threshold, T	**PSNR(dB) for the restored image of 40% noisy Lenna**
T=510	17.02
T=510*0.8	17.54
T=(510*0.8)*0.8	17.93

So, for ensuring high accuracy of the detection, we applied our method recursively and iteratively with decreasing threshold (T=T*0.8), starting with the value T=510, and iterated until T ≥ arithmetic mean of all the pixel values on the minimum direction of the corresponding window.

4. RESULTS

Two gray level and two color (RGB) benchmark images have been taken for the experimental purpose. Noises have been injected randomly into the original images to produce noisy images. The enhancement filter generated restored images from these noisy images. Figure 2.a and 2.b are original benchmarked Elaine and Lenna gray images. Figure 2.c and 2.d are original benchmarks, Lenna and Baboon color images. Figure 2.e, Figure 2.g are the noisy images, with 40% and 60% noise density, of Lenna where PSNR is 13.93dB and 12.57dB respectively that of Figure 2.f and Figure 2.h are the filtered image using MDWCMMF where the PSNR is 24.45 dB and 21.46 dB respectively. Figure 2.i shows 40% corrupted Elaine benchmark image whose PSNR value is 14.13 dB but when MDWCMM filter has been applied on it, the PSNR obtained is 24.86 dB (Figure 2.j). Figure 2.m shows 3% corrupted Baboon (RGB) benchmark image whose PSNR value is 24.07 but when MDWCMM filter has been applied on it, the PSNR obtained is 26.76(Figure 2.n). Figure 2.k shows 30% noise integrated image where PSNR is 14.49. Application of MDWCMMF on it PSNR increases to 24.01 (Figure. 2.l) from where we may infer that MDWCMM filter may obtain good results in random and high noise removal from gray and color images.

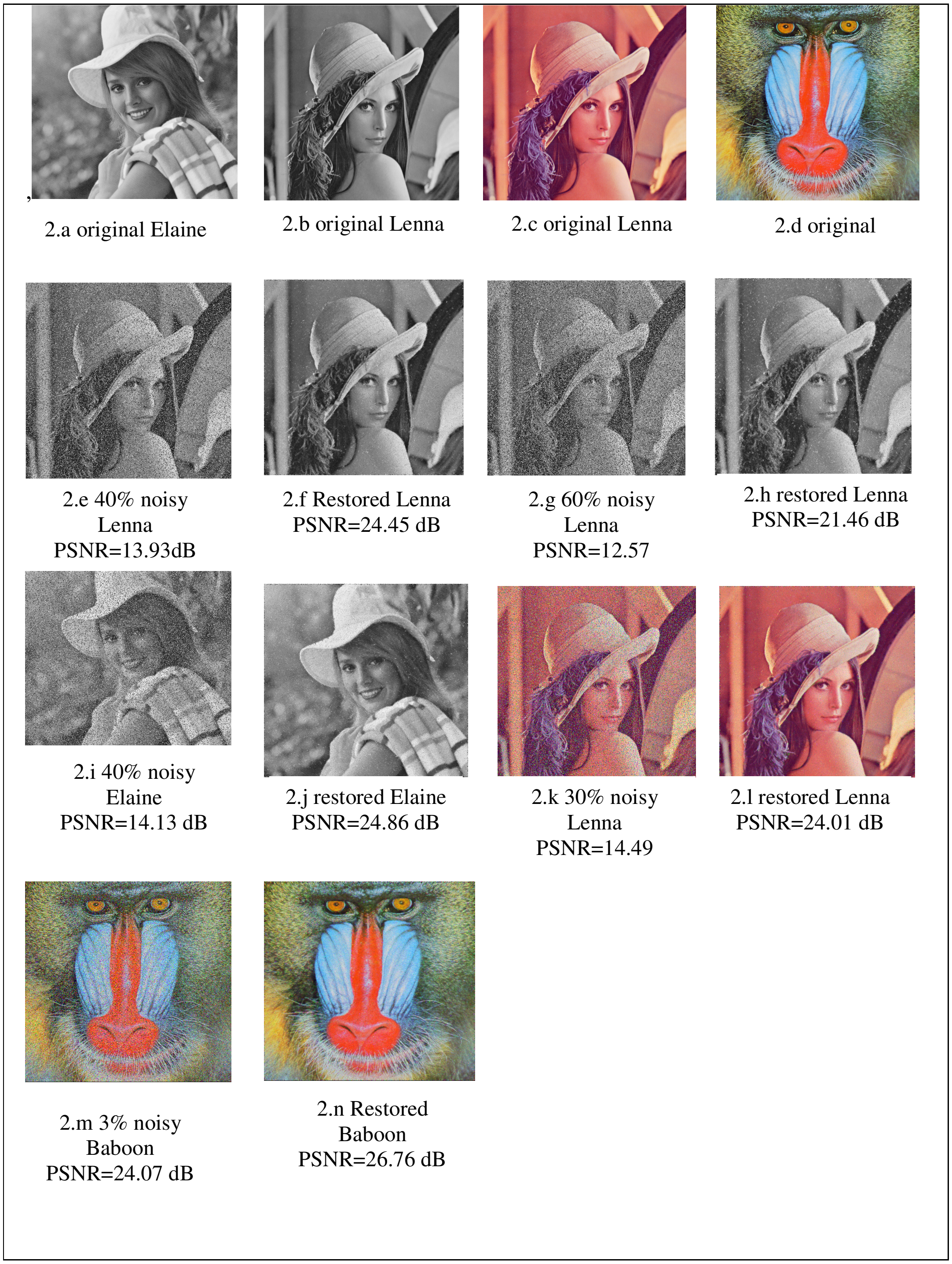
Table 2 shows the comparative PSNR using various filters PWMAD[3], ACWM filter[1,2], AMF[7] including proposed MDWCMM filter applied on Lenna gray image corrupted by various percentages of noise density.

Table 3 and Table 4 shows the comparative PSNR using various filters AVMF[26], IIA[16], MFF[19], ATMED[21], GMED[21], TMAV[21], FSB[25], IFCF[23], MIFCF[23], EIFC[23], SSFCF[23], FIRE[17], PWLFIRE[18], DSFIRE[15], FMF[21], HAF[24], AWFM[22], including proposed MDWCMM filter applied on color Baboon image and color Lenna image corrupted by various percentages of noise density, respectively.

Table 5 shows the effect of applying MDWCMM filter of various images corrupted by 40% noise. From the table it is also clear that the MDWCMM filter works better for high value of random impulse noise.

Figure 3. shows the comparative performance of the proposed filter applied on gray Lenna corrupted with different levels of impulses among some other existing filters.

Figure 4. shows the comparative performance of the proposed filter applied on Elaine and Goldhill images corrupted with 40% impulses among some other existing filters.



2.a original Elaine

2.b original Lenna

2.c original Lenna

2.d original

2.e 40% noisy Lenna PSNR=13.93dB

2.f Restored Lenna PSNR=24.45 dB

2.g 60% noisy Lenna PSNR=12.57

2.h restored Lenna PSNR=21.46 dB

2.i 40% noisy Elaine PSNR=14.13 dB

2.j restored Elaine PSNR=24.86 dB

2.k 30% noisy Lenna PSNR=14.49

2.l restored Lenna PSNR=24.01 dB

2.m 3% noisy Baboon PSNR=24.07 dB

2.n Restored Baboon PSNR=26.76 dB

Figue 2.Visual effect of results using MDWCMMF on gray and color images.

Table 2. Comparative results in PSNR of different algorithms applied to “Lenna” gray image corrupted by various rayes of Random-valued impulse noise

Filters	**PSNR of restored image in dB**					
	10% Noise	**20% Noise**	**30% Noise**	**40% Noise**	**50% Noise**	**60% Noise**
PWMAD	34.86	30.58	25.94	22.41	19.42	17.08
ACWM filter	-	36.07	32.59	28.79	25.19	21.19
AMF	28.06	26.79	24.03	23.17	21.99	-
Proposed	31.14	28.16	26.08	24.45	22.96	21.46

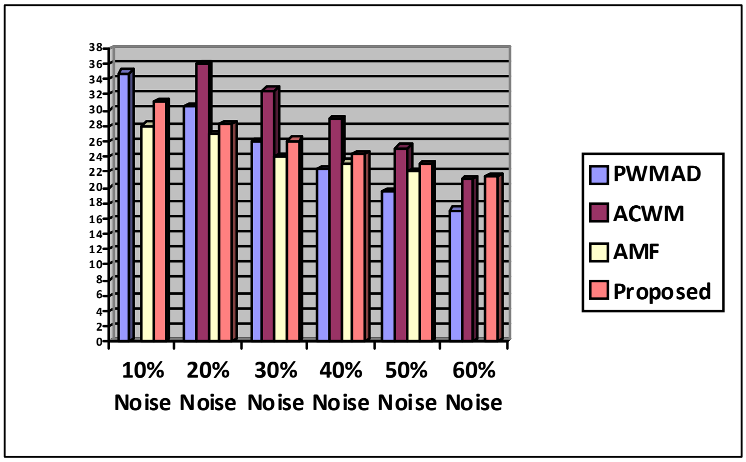


Figure 3. Comparison among various filters applied on gray Lenna corrupted with different levels of impulses

Table 3. Comparative results in PSNR of different algorithms applied to “Baboon” COLOR image corrupted by various rates of Random-valued impulse noise

Filters	**PSNR of restored image in dB**						
	3%	**5%**	**10%**	**15%**	**20%**	**25%**	**30%**
AVMF	27.4	26.0	25.1	24.3	22.9	21.5	20.3
MFF	25.0	24.9	24.4	23.6	22.5	21.2	19.8
ATMED	24.4	24.3	24.0	23.7	23.5	23.2	22.2
GMED	24.7	24.6	24.2	23.7	23.0	22.0	20.7
TMAV	24.8	24.7	24.4	23.8	23.0	21.9	20.7
FSB	24.6	24.5	24.1	23.6	22.9	21.9	20.9

IFCF	24.8	24.7	24.1	23.5	22.8	22.0	20.7
MIFCF	25.2	25.0	24.2	23.2	22.2	20.9	19.6
EIFCF	24.9	24.7	24.0	23.4	22.7	21.7	20.7
SSFCF	24.8	24.6	24.0	23.1	21.9	20.5	19.0
FIRE	28.3	27.5	25.6	23.5	21.6	19.8	18.2
PWLFIRE	37.7	34.8	29.3	25.3	22.3	19.8	17.9
DSFIRE	33.2	32.4	30.7	29.0	27.6	25.9	24.2
FMF	32.0	30.3	27.7	25.8	24.2	22.6	21.0
HAF	24.6	24.5	24.4	24.3	24.2	24.1	23.9
AWFM	25.0	24.8	24.4	24.1	23.8	23.5	23.2
Proposed	26.76	26.18	24.94	23.97	23.13	22.41	21.77

Table 4. Comparative results in PSNR of different algorithms applied to "Lenna" COLOR image corrupted by various rayes of Random-valued impulse noise

Filters	**PSNR of restored image in dB**						
	3%	**5%**	**10%**	**15%**	**20%**	**25%**	**30%**
AVMF	37.3	36.2	33.9	32.1	30.3	27.8	25.6
IIA	34.3	33.5	30.6	27.3	24.9	23.5	22.0
MFF	28.8	28.5	27.8	27.0	26.1	25.0	23.8
ATMED	30.3	29.9	28.8	27.8	26.6	25.3	24.1
GMED	31.2	31.0	30.1	29.3	28.2	26.7	25.3
TMAV	31.0	30.7	29.8	28.7	27.4	25.9	24.5
FSB	30.7	30.6	29.8	29.1	28.1	26.6	25.3
IFCF	30.7	30.4	29.4	28.7	27.8	26.6	25.6
MIFCF	30.9	30.6	29.4	28.5	27.4	26.1	25.0
EIFCF	30.5	30.3	29.4	28.7	27.8	26.6	25.6
SSFCF	30.3	30.1	29.3	28.4	27.1	25.6	24.2
FIRE	34.3	32.6	29.7	27.6	25.7	23.9	22.4
PWLFIRE	31.1	28.8	25.5	23.4	21.7	20.4	19.1
DSFIRE	30.5	28.6	25.8	24.1	22.7	21.6	20.6

FMF	36.4	24.8	31.9	30.2	28.5	26.4	24.9
HAF	29.6	29.2	27.8	26.6	25.2	24.0	22.7
AWFM	31.3	30.8	29.3	28.0	26.2	24.7	23.1
Proposed	34.98	33.38	30.70	28.98	27.66	26.56	25.62

Table 5. comparative results in PSNR of different algorithms applied to various kinds of gray images corrupted with 40% of random-valued impulse noise

Filters	**PSNR of restored image in dB**			
	Elaine	**Goldhill**	**Pepper**	**Airplane**
PWMAD	24.66	24.16	24.63	24.37
Trilateral	19.38	19.14	19.53	19.54
TSM	20.26	20.02	20.14	19.37
Proposed	24.86	24.88	23.96	23.20

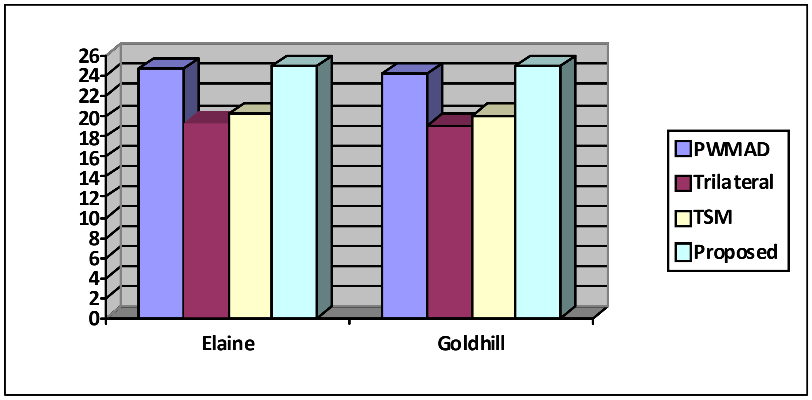


Figure 4. Comparison among various filters applied on various images corrupted with 40% noise

5. CONCLUSIONS

In this paper, we proposed a new directional weighted cascaded mask median-based filter, for removing random-valued impulse noise. It makes full use of the characteristics of impulse and edges to detect and restore noise. Since PSNR represents the ratio between the maximum possible power of a signal and the power of corrupting noise, the higher value of PSNR for filtered image than the PSNR value for the corrupted image gives better result .Simulation results showed that this filter performs much better than many existing median-based filters in both subjective and objective (PSNR) evaluations.

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REFERENCES

[1] Yiqiu Dong and Shufang Xu , “A New Directional Weighted Median Filter for Removal of Random-Valued Impulse Noise”,IEEE SIGNAL PROCESSING LETTERS, VOL. 14, NO. 3, MARCH 2007

[2] T. Chen and H. R. Wu, “Adaptive impulse detection using center-weighted median filters,” IEEE Signal Process. Lett., vol. 8, no. 1, pp. 1–3, Jan. 2001.

[3] V. Crnojevi´c, V. ˇSenk and ˇ Z. Trpovski, “Advanced impulse detection based on pixel-wise MAD,” IEEE Signal Processing Letters, vol. 11, pp. 589–592, 2004.

[4] Waqas Nawaz, Arfan Jaffar, and Ayyaz Hussain,” Fast Directional Weighted Median Filter for Removal of Random-Valued Impulse Noise”, 978-1-4244-8003-6/10/$26.00 ©2010 IEEE.

[5] X. Li and M. Orchard, “True edge-preserving filtering for impulse noise removal,” in presented at the 34th Asilomar Conf. Signals, Syst. Comput.,Pacific Grove CA, Oct. 2000.

[6] Sheng-Fu Liang, Shih-Mao Lu, Jyh-Yeong Chang, Chin-Teng (CT) Lin , “A Novel Two-Stage Impulse Noise Removal Technique Based on Neural Networks and Fuzzy Decision” IEEE TRANSACTIONS ON FUZZY SYSTEMS, VOL. 16, NO. 4, AUGUST 2008 863

[7] Wang H, Haddad R A, Adaptive median filters: New algorithms and results, IEEE Transactions on Image Processing, vol. 4, 1995, pp 499-502.

[8] Tao Chen, Kai-Kuang Ma and Li-Hui Chen (1999), ‘Tri-State Median Filter for Image Denoising’, IEEE Trans. on Image Processing, Vol. 8, No.8, pp.1-3, 1999.

[9] T. Chen and H. R. Wu, “Space variant median filters for the restoration of impulse noise corrupted images”, IEEE Trans. Circuits Syst. II, vol. 48, no. 8, pp. 784-789, Aug. 2001.

[10] W. K. Pratt, “Median filtering,” Image Process. Inst., Univ. Southern California, Los Angeles, Sep. 1975, Tech. Rep..

[11] S. Zhang and M. A. Karim, “A new impulse detector for switching median filters,” IEEE Signal Process. Lett., vol. 9, no. 11, pp. 360-363, Nov. 2002.

[12] Pankaj Kr. Sa, Ratnakar Dash, Banshidhar Majhi,“Second order difference based detection and directional weighted median filter for removal of random valued impulse noise”, 4th IEEE International Conference on Industrial & Information Science, 28-31 Dec. 2009.

[13] E. Abreu, M. Lightstone, S. K. Mitra, and K. Arakawa, “Anew efficient approach for the removal of impulse noise from highly corrupted images”, IEEE Trans. Image Process., vol. 5, no. 6, pp. 1012-1025, Jun. 1996.

[14] V. Crnojevic, V. Senk, and Z. Trpovski, “Advanced Impulse Detector Based on Pixel-Wise MAD” IEEE Signal Processing Letters, vol. 11, no. 7, pp.589-592, July 2004.

[15] S. Schulte, V. D. Witte, M Nachtegael, D.V. D. Weken, and E.E. Kerre,”Fuzzy two-step filter for impuldse noise reduction from color images”, IEEE transactions on image processing, vol. 15, no. 11, Nov. 2006.

[16] S. M. Guo, C. S. Lee, and C. Y. Hsu, “An intelligent image agent based on soft-computing techniques for color image processing”, Expert Syst. Appl., vol. 28, pp. 483-494, Apr 2005.

[17] F. Russo and G. Ramponi,”A fuzzy filter for image corrupted by impulse noise”, IEEE Signal Processing Letters, vol. 3, no. 6, pp.168-170, Jun 1996.

[18] F. Russo, “Fire operators in image procesing”, Fuzzy Sets and Syst., vol. 103, pp. 265-275,Apr 1999.

[19] F. Russo and G. Ramponi,”A noise smoother using cascaded FIRE filters”, in proc. IEEE 4th Int. Conf. Fuzzy Systems, vol. 1, pp.351-358, Mar. 1995.

[20] K. Arakawa, “Median filter based on fuzzy rules and its application to image restoration”, Fuzzy Sets and Syst., vol. 77, pp. 3-13, Jun 1996.

[21] H.K. Kwan, “Fuzzy filters for noise reduction in image”, in Fuzzy filters for image processing, M. Nachtegael, D. Van der Weken, D. Van De Ville, and E. E. Eds, 1st Ed., Heidelberg, Germany: Physica Verlag, 2003, vol. 122, pp. 25-53.

[22] C. S. Lee, Y. H. Kuo, and P.T.Yu, “Weighted fuzzy mean filters for image processing”, Fuzzy Sets and Syst., vol. 89, pp. 157-180, Jun 1997.

[23] F. Ferbiz, M. B. Menhaj, and S.A. Motamedi, “Edge preserving image filtering based on fuzzy logic”, in proc. 6th EUFIT conf., 1998, pp. 1417-1421.

[24] H.G. Wang and H.C.Chiu, “An adaptive fuzzy filter for restoring highly corrupted images by histogram estimation”, in Proc. Nat. Sci. Council Part A, 1999, vol. 23, pp. 630-643.

[25] I. Kalaykov and G. Tolt, M M. Nachtegael, D. Van der Weken, D. Van De Ville, and E. E. Eds,”Real-time image noise cancellation based on fuzzy similarity”, 1st Ed., Heidelberg, Germany: Physica Verlag, 2003, vol. 122, pp. 54-71.

[26] R. Lukac, “Adaptive vector median filter”, Pattern Recognit. Lett., vol. 24,pp. 1889-1899, Aug. 2003.

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