Research on the decision-based adaptive weighted mean filter algorithm for impulse noise removal

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Abstract

The decision-based adaptive weighted mean filter is proposed to remove impulse noise from the highly corrupted image. The proposed filter first identifies the corrupted pixels using the soft decision-based noise detector and then removes the detected impulses using the adaptive weighted mean filter while keeping the uncorrupted pixels unaltered. Extensive simulations indicate that the proposed filter significantly outperforms a number of existing decision-based filters in that it can remove impulse noise from the corrupted image effectively while preserving the details in the image very well.

Keywords: mean filter, impulse noise, noise detector

1 Introduction

Images are often corrupted by impulse noise in the process of transmission over noisy communication channels or recording by noisy sensors [1]. The median filter, a kind of effective nonlinear filter, has been widely used for removing impulse noise because of its superior performance in noise suppression and edge preservation in comparison with the linear filters [2, 3]. However, the standard median (MED) filter is implemented uniformly across the entire image without taking account of whether a pixel is corrupted or not. Inevitably, the MED filter will modify both noise pixels and undisturbed good pixels, thus causing the blurring or loss of fine details in the image [4, 5].

To prevent the alteration of good pixels, switching-based filters realized using thresholding operations have been studied recently [6-18]. In the switching filtering schemes, the noise detector is firstly used to classify the pixels in the image as the corrupted pixels or noise-free pixels and then filtering is activated for the detected corrupted pixels. Among the various switching-based filters are Progressive Switching Median (PSM) filter [6], Recursive Adaptive Center Weighted Median (RACWM) filter [9], Non-recursive Adaptive Center Weighted Median (NACWM) filter [9], Noise Adaptive Soft-switching Median (NASM) filter [10], Laplacian Detector-based Switching Median (LDSM) filter [11], pixel-wise MAD-based (PWMAD) filter [14], Opening Closing Sequence (OCS) filter [17] and Fast Switching Median (FSM) filter [18]. At a relatively low noise ratio, these filters can perform better than the MED filter by removing impulse noise while preserving the fine details very well. However, they tend to damage the details or retain too much impulse noise in the image at a high noise ratio.

To restore the highly corrupted image effectively, the decision-based adaptive weighted mean (DAWM) filter is proposed in this letter. Different from many well known decision-based filters, the proposed filter uses the progressive noise detector to identify the corrupted pixels and adopts the adaptive weighted mean filter to remove the detected impulse noises. By combining this novel noise detector with the distinctive mean filter, the DAWM filter achieves significantly better restoration performance than many other decision-based filters at the various noise ratios, especially when the image is highly corrupted by impulse noise.

2 DAWM filter

2.1 NOISE DETECTION

The DAWM filter realizes the noise detection progressively using two varying detection thresholds T_l and T_h. Let $f_{i,j}$ be the value of the noise image at pixel location (*i,j*) and $b_{i,j}$ be the noise flag of the pixel (*i,j*). Prior to noise detection, $b_{i,j}$ is predefined as 2 for all the pixels in the image to indicate that they are indefinite pixels and need to be identified. T_l and T_h are initialized with a small value T_s and a big one T_b ($T_b > T_s$), respectively.

In the process of progressive noise detection, for any indefinite pixel (*i,j*) with $b_{i,j}$ =2 all the pixels in the $(2L_d+1)\times(2L_d+1)$ detection window centered about it are considered. Let $W_{i,j}$ denote the samples in this window, i.e.,

$$W_{i,j} = \{ f_{i+s,j+t} \mid b_{i,j} = 2, -L_d \le s,t \le L_d \}. \tag{1}$$

Let the maximum pixel value and the minimum value in $W_{i,j}$ be $f_{i,j}^{\max}$ and $f_{i,j}^{\min}$, respectively. The set $N_{i,j}$ comprising of $f_{i,j}^{\max}$ and $f_{i,j}^{\min}$ is expressed as $N_{i,j} = \{ f_{i,j}^{\max}, f_{i,j}^{\min} \}$. Because the corrupted pixel usually has higher or lower value than that of its neighbouring noise-free pixels, the pixel (*i,j*) will be identified as noise-free pixel with $b_{i,j}=0$ if $f_{i,j} \notin N_{i,j}$ or noise candidate if $f_{i,j} \in N_{i,j}$.

However, the above decision method will misclassify the noise-free pixel with its value in the set $N_{i,j}$ as noise candidate. To address this problem, the local statistics, the absolute deviation from the median value, is adopted to correct the misclassified noise candidate. Let the median value of $W_{i,j}$ be $m_{i,j}$. The absolute deviation from this value is defined as $d_{i,j} = | f_{i,j} - m_{i,j} |$. The soft decision scheme is adopted to reclassify the noise candidate as corrupted pixel with $b_{i,j}$ =1, noise-free pixel with $b_{i,j}$ =0 or indefinite pixel with $b_{i,j}$ =2.

$$b_{i,j} = \begin{cases} 1 & d_{i,j} \ge T_h \\ 2 & T_l \le d_{i,j} < T_h \\ 0 & d_{i,j} < T_l \end{cases}. \tag{2}$$

The corrupted pixel will be processed by the recursive median filter, which means that current pixel is dependent on the new values instead of the old ones of previously processed pixels. The output of the recursive median filter is obtained by:

$$f_{i,j} = (1 - |b_{i,j} - 1|) \cdot m_{i,j} + (|b_{i,j} - 1|) f_{i,j}. \tag{3}$$

From Eq. (3), it can be seen that only the corrupted pixel is processed and its value is replaced with $m_{i,j}$ while the noise-free pixel or indefinite pixel will be left unchanged. It should be mentioned that the recursive median filter is only used for assisting with the noise detection and thus its output will not be used as the final restoration result which will be gotten using the subsequent adaptive weighted mean filter.

When noise detection is implemented for all the pixels in the image, two detection thresholds T_l and T_h will be updated in the following way.

$$T_l \leftarrow T_l + 1, \tag{4}$$

$$T_h \leftarrow T_h - 1. \tag{5}$$

The above noise detection process will be iteratively implemented to classify the indefinite pixels further provided that T_l is smaller than T_h. When T_l exceeds T_h, the progressive noise detection process terminates and the noise ratio R can be roughly estimated.

$$R = \frac{S}{M \times N}, \tag{6}$$

where S denotes the number of the noise pixels while M and N denote the total number of pixels.

2.2 NOISE REMOVAL

The detected impulses will be removed by adaptive weighted mean filter. Let $f'_{i,j}$ be the value of the noise image at pixel location (*i,j*). For the corrupted pixel (*i, j*), the filtering window of size $(2L_f + 1) \times (2L_f + 1)$ is used. Starting with L_f =1, this filtering window iteratively extends outward by one pixel in its four sides until the number of noise-free pixels (denoted by $P_{i,j}$) within this window is not less than 1. Let $W'_{i,j}$ denote the values of noise-free pixels in the filtering window, i.e.,

$$W'_{i,j} = \{ f'_{i+s,j+t} \mid b_{i+s,j+t} = 0, b_{i,j} = 1, \\ (s,t) \ne (0,0), -L_f \le s,t \le L_f \}. \tag{7}$$

The weighted mean value $g_{i,j}$ of the pixel values in $W'_{i,j}$ is defined as:

$$g_{i,j} = \frac{\sum_{f_{i+s,j+t} \in W'_{i,j}} w_{i+s,j+t} f'_{i+s,j+t}}{\sum_{f_{i+s,j+t} \in W'_{i,j}} w_{i+s,j+t}}, \tag{8}$$

where $w_{i+s,j+t}$ means the weight of $f'_{i+s,j+t}$. Let $m'_{i,j}$ be the median value of $W'_{i,j}$. Because the median value has the least probability to be the value of the corrupted pixels [1], $m'_{i,j}$ is utilized to determine $w_{i+s,j+t}$. It is easy to understand that the smaller the absolute difference between $f'_{i+s,j+t}$ and $m'_{i,j}$, the larger the weight $w_{i+s,j+t}$ should be to strengthen the influence of $f'_{i+s,j+t}$ on $g_{i,j}$. Based on extensive simulations, which indicate that $w_{i+s,j+t}$ is dependant on both above absolute difference and noise ratio, $w_{i+s,j+t}$ is chosen as:

$$w_{i+s,j+t} = \frac{R}{R + (1-R)\sqrt{\dfrac{\dfrac{|f'_{i+s,j+t} - m'_{i,j}|}{f'_{\max} - f'_{\min}}}{1 - \dfrac{|f'_{i+s,j+t} - m'_{i,j}|}{f'_{\max} - f'_{\min}}}}}, \tag{9}$$

where $f'_{\max}$ and $f'_{\min}$ denote the maximum pixel value and the minimum one in the noise image, respectively.

The output of the DAWM filter is obtained by:

$$h_{i,j} = b_{i,j} \cdot g_{i,j} + (1 - b_{i,j}) f'_{i,j}. \tag{10}$$

3 Experimental results

In this section, the proposed DAWM filer is evaluated and compared with the MED filter, PSM filter, NACWM filter, RACWM filter, NASM filter, LDSM filter, PWMAD filter, OCS filter and FSM filter. Two 512 × 512 gray-level test images *Lena* and *Bridge* with distinctly different features are used for the experiments. Extensive simulations are conducted on the two test images corrupted by the salt-pepper impulses with a wide range of noise densities varying from 10% to 80%. In the DAWM filer, we set $L_d = 3$ while T_s and T_b are predefined as 15 and 35, respectively. For the other compared filters, the filtering window size is adaptively chosen to ensure the best filtering performance at the various noise densities. Here, the filtering performance is quantitatively measured by the peak signal-to-noise ratio (PSNR) as in [17, 18].

Table 1 and Table 2 list the PSNR values of all the evaluated filters operating on the corrupted images *Lena* and *Bridge*, respectively. It can be seen clearly from the Tables 1 and 2 that the DAWM filter produces higher PSNR values than other compared filters at the various noise ratios. Indeed, the objective evaluation based on PSNR measurement demonstrates that the DAWM filter has the best filtering performance among all these filters.

The subjective visual comparisons are also made among the filtering results of the DAWM filter and three recently proposed filters, namely, PWMAD filter, OCS filter and FSM filter. Figure 1 and Figure 2 show the restoration results of these filters operating on the two test images corrupted by 70% salt-pepper noise. From Figs. 1 and 2, it is easy to see that PWMAD filter leave numerous impulses in the filtered image and lead to the blurring of the image. The OCS filter and FSM filter cause the loss of some details although they suppress impulse noise better than the PWMAD filter. The proposed filter first identifies the corrupted pixels using the soft decision-based noise detector and then removes the detected impulses using the adaptive weighted mean filter while keeping the uncorrupted pixels unaltered. The DAWM filter provides better restoration results than these filters in that it not only removes the impulses effectively but also preserves the fine details very well.

TABLE 1 Comparison of restoration performance in PSNR (dB) for the evaluated filters operating on Lena

Filters	**Noise density**							
	10%	20%	30%	40%	50%	60%	70%	80%
MED	34.32	30.39	29.67	28.17	26.84	24.67	22.90	19.45
PSM	39.72	35.99	33.57	31.38	30.17	27.40	24.54	20.88
NACWM	39.80	34.83	33.04	30.03	28.42	26.64	23.29	19.86
RACWM	40.54	36.56	33.56	30.70	29.12	27.21	23.54	19.92
NASM	37.92	35.63	33.64	31.34	29.20	26.52	23.93	20.44
LDSM	39.68	34.36	32.80	29.76	28.03	26.28	23.06	19.56
PWMAD	39.74	33.49	31.96	29.39	27.92	26.34	23.15	19.71
OCS	30. 81	31.30	31.36	31.20	30.86	30.55	29.51	27.95
FSM	38.93	36.33	34.28	32.35	30.70	29.07	27.44	25.20
DAWM	42.75	39.78	37.64	35.69	34.21	32.55	30.92	29.13

TABLE 2 Comparison of restoration performance in PSNR (dB) for the evaluated filters operating on bridge

Filters	**Noise density**							
	10%	20%	30%	40%	50%	60%	70%	80%
MED	26.18	24.62	23.25	22.53	21.61	20.74	19.51	17.20
PSM	30.53	28.14	25.80	24.56	23.54	22.21	21.26	18.23
NACWM	31.34	27.49	25.36	24.18	22.75	21.56	19.91	17.30
RACWM	31.62	28.29	26.25	24.36	23.87	21.44	19.52	16.40
NASM	28.23	27.04	26.24	24.83	23.33	21.88	19.98	17.56
LDSM	31.42	27.80	26.14	24.32	22.93	21.60	20.02	17.42
PWMAD	30.99	26.86	25.18	23.75	22.50	21.28	19.81	17.36
OCS	24.03	24.32	24.40	24.32	24.14	23.81	23.19	22.07
FSM	29.60	28.54	27.10	25.75	24.49	23.41	22.37	21.13
DAWM	33.62	31.88	30.00	28.32	26.81	25.52	24.32	23.10

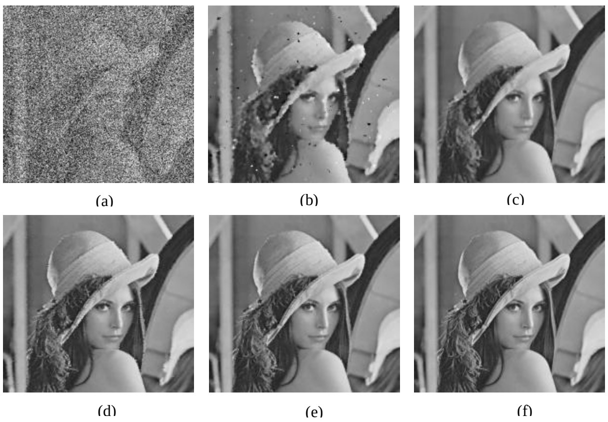

FIGURE 1 Restoration results using various filters for Lena corrupted by 70% impulse noise: (a) Corrupted Lena, (b) PWMAD filter, (c) OCS filter, (d) FSM filter, (e) DAWM filter, (f) Original Lena

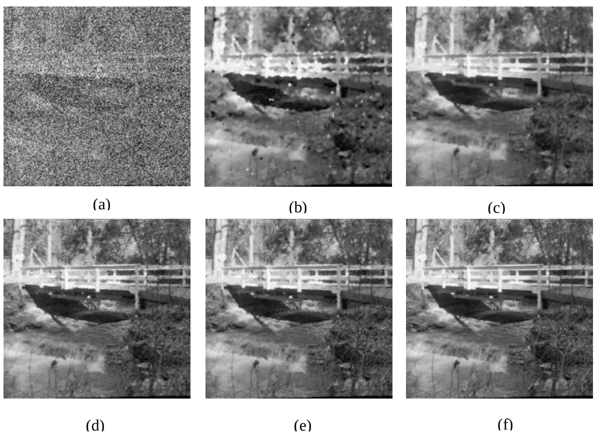

FIGURE 2 Restoration results using various filters for Bridge corrupted by 70% impulse noise: (a) Corrupted Bridge, (b) PWMAD filter, (c) OCS filter, (d) FSM filter, (e) DAWM filter, (f) Original Bridge

5 Conclusions

In this letter, we present an efficient decision-based adaptive weighted mean filter for impulse noise removal. The proposed filter realizes noise detection progressively using the soft decision-based noise detector and suppresses the detected impulse noise by the adaptive weighted mean filter. The performance of the proposed filter has been extensively compared with those of many well known techniques. Experimental results indicate that the proposed filter achieves the best trade-off between noise removal and detail preservation among all the evaluated filters and it also provides outstanding robustness in combating a wide variation of noise densities. With the experiment, the proposed filter first identifies the corrupted pixels using the soft decision-based noise detector and then removes the detected impulses using the adaptive weighted mean filter while keeping the uncorrupted pixels unaltered. The DAWM filter provides better restoration results than these filters in that it not only removes the impulses effectively but also preserves the fine details very well.

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References

[1] Gonzalez R C, Woods R E 2001 *Digital image processing* 2nd ed, Englewood Cliffs, NJ: Prentice-Hall 164-7
[2] Pitas I, Venetsanopou A 1990 *Nonlinear Digital Filters: Principles and Application* Norwell, MA: Kluwer 277-9
[3] Huang T S, Yang G J, Tang G Y 1979 Fast two-dimensional median filtering algorithm *IEEE Trans Acoust Speech Signal Process* **1** 8–13
[4] Nodes T A, Gallagher Jr N C 1984 The output distribution of median type filters *IEEE Trans Commun* **32** 532–41
[5] Sun T, Neuvo Y 1994 Detail-preserving median based filters in image processing *Pattern Recognit Lett* **15** 341–7
[6] Wang Z, Zhang D 1999 Progressive switching median filter for the removal of impulse noise from highly corrupted images *IEEE Trans Circuits Syst-II: Analog Digital Signal Process* **46** 78–80
[7] Chen T, Ma K, Chen L 1999 Tri-state median filter for image denoising *IEEE Trans Image Process* **8** 1834–8
[8] Chen T, Wu H R 2001 Space variant median filters for the restoration of impulse noise corrupted images *IEEE Trans Circuits Syst-II: Analog Digital Signal Process* **48** 784–9
[9] Chen T, Wu H R 2001 Adaptive impulse detection using center-weighted median filters *IEEE Signal Process Lett* **8** 1-3
[10] Eng H L, Ma K K 2001 Noise adaptive soft-switching median filter *IEEE Trans Image Process* **10** 242–51
[11] Zhang S, Karim M A 2002 A new impulse detector for switching median filters *IEEE Signal Process Lett* **9** 360–3
[12] Hashimoto Y, Kajikawa Y, Nomura Y 2002 Directional difference based switching median filters *Electron. Commun* **85** 22–32
[13] Pok G, Liu J, Nair A 2003 Selective removal of impulse noise based on homogeneity level information *IEEE Trans Image Process* **12** 85–92
[14] Crnojevic V, Senk V, Trpovski Z 2004 Advanced impulse detection based on pixel-wise MAD *IEEE Signal Process Lett* **11** 589–92
[15] Garnett R, Huegerich T, Chui C, He W 2005 A universal noise removal algorithm with an impulse detector *IEEE Trans Image Process* **14** 1747–54
[16] Chan R H, Ho C W, Nikolova M 2005 *Salt-and-pepper noise removal by median-type noise detectors and detail-preserving regularization* **14** 1479-85
[17] Deng Z F, Yin Z P, Xiong Y L 2007 High probability impulse noise-removing algorithm based on mathematical morphology *IEEE Signal Process Lett* **14** 31-4
[18] Srinivasan K S, Ebenezer D 2007 A new fast and efficient decision-based algorithm for removal of high-density impulse noises *IEEE Signal Process Lett* **14** 189-92

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