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Impulse Noise Detection and Filtering Based On Adaptive Weighted Median Filter

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Abstract— *Improved Impulse noise Detector (IID) for Adaptive Switching Median (ASWM) filter is presented. The idea behind the improved impulse noise detection scheme is based on normalized absolute difference with in the filtering window, and then removing the detected impulse noise in corrupted images by using ASWM filter. This detection scheme distinguishes the noisy and noise-free pixels efficiently. A weighted median filter, based on standard deviation within the filtering window is used in ASWM filtering. The application of absolute difference, will distinguishes the difference between a noise free and noisy pixel more precisely. The proposed scheme results in efficient detection of noisy pixels. Extensive simulation results show that the proposed scheme significantly outperforms in terms of PSNR and MAE than many other variant types of median filter for random-valued impulse noise. More over IID scheme provides better noise detection performance*.

Index Terms—*Image filtering, Absolute difference, Peak Signal to Noise Ratio (PSNR), Mean Absolute Error (MEA), Median filter, .impulse detector*

I. Introduction

Digital images are frequently affected by impulse noise during their acquisition or transmission in a noisy environment [1]. Therefore, to efficiently remove noise from an image while preserving its features is a fundamental problem of image processing [2]. The impulse noise can be classified either as salt-and-pepper with noisy pixels taking either maximum or minimum value, or as random valued impulse noise. The removal of fixed-valued impulse noise has been widely studied and a large number of algorithms have been proposed [1]–[5]. The median filter is the most popular choice for removing the impulse noise from images because of its effectiveness and high computational efficiency. However, when the median filtering is carried out for every pixel across the image, it modifies both noisy as well as noise-free pixels. Consequently, some desirable details are also removed from the images. In order to overcome this drawback of median filter, many filtering algorithms with an impulse detector have been proposed, such as tri-state median (TSM) filter [3], the pixel-wise MAD (PWMAD) filter [4], and center-weighted median (CWM) filter [5], etc. The performance of these filters is dependent on the capabilities of the detectors employed in the filtering schemes. In case of random valued impulse noise, the detection of an impulse is relatively more difficult in comparison with salt-and-pepper impulse noise. Hence, the performance of most of the filters is not good when the impulse noise is random-valued. In, this letter, a new scheme based on contrast enhancement in the filtering window through a nonlinear function is presented, which exhibits significantly improved impulse detection capability in case of random-valued impulse noise. Impulse detection and filtering operations are performed in an iterative manner. Most of the iterative filtering schemes available in the literature do not have any suitable criterion to determine the number of iterations for optimum performance. We have proposed an effective stopping criterion based on noisy image characteristics to determine the number of iterations. The letter is organized as follows. In Section II, we introduce the proposed detection scheme and filtering framework. Section III presents a number of experimental results that demonstrate the performance of the proposed scheme. Finally, Section IV provides the concluding remarks.

II. Impulse Noise Detection And Filtering

The impulse detection is based on the assumption that a noise free image contains locally smoothly varying areas separated by edges. Let the image of size $M X N$ has 8-bit gray scale pixel Resolution, that is $I \in [0,255]$, . In a $(2L+1) X (2L+1)$ window $W^{(x)}(i, j)$ at location (i, j), the center pixel value is denoted as $x(i, j)$, and L is an integer. We assume the following impulse noise model, with noise probability p:

$$x\,(i,j)=\begin{cases} o_{ij},\ with & probability \quad 1-p \\ n_{ij},\ with & probability \quad p \end{cases}$$

where $o_{i,j}$ and $n_{i,j}$ denote the pixel values at location *(i,j)* in the original uncorrupted image and the noisy image, respectively. The noisy pixel value, $n_{i,j}$, is uniformly distributed between the minimal (0) and maximal (255) possible pixel values.

A. Impulse Detection

In an image contaminated by random-valued impulse noise, the detection of noisy pixel is more difficult in comparison with fixed valued impulse noise, as the gray value of noisy pixel may not be substantially larger or smaller than those of its neighbors. Due to this reason, the conventional median-based impulse detection methods do not perform well in case of random valued impulse noise. In order to overcome this problem, we use a non linear function to transform the pixel values within the filter window $W^{(x)}(i,j)$ in a progressive manner. This operation widens the gap between noisy pixel $x\,(i,j)$ and the other pixels in the window $W^{(x)}(i,j)$. In the beginning of each iteration, the central pixel $x\,(i,j)$ of each window is subtracted from all the pixels in the window and normalized absolute differences are obtained

$$d(m,n)=\left|x(m,n)-x(i,j)\right|/\,255;\,x(m,n)\in W^{(x)}(i,j)\cdots\cdots 2$$

$$\text{Where}\ m=i-L,...,i+L, n=j-L,...,j+L\cdots\cdots(3)\,.$$

The normalized absolute differences, are then transformed by a nonlinear function to increase the gap between the differences *d(m, n)* corresponding to noisy pixels and those due to noise-free Pixels

$$d^{(t)}(m,n)=e^{K.d(m,n)}-1;$$

$$m=i-L,...,i+L, n=j-L,...,j+L\cdots\cdots(4)$$

where $d^{(t)}(m,n)$ denotes the transformed value of $d(m,n)$and K is a constant which varies with iterations. The transformed values $d^{(t)}(m,n)$ are sorted as $\{d^{(t)}(1)\leq d^{(t)}(2)\leq \ldots \leq d^{(t)}(9)\}$in ascending order where $\{ d^{(t)}(1), d^{(t)}(2), \ldots, d^{(t)}(9)\}$ are the transformed values$\{d(m,n)\}$ of . Now, the central pixel is considered noisy for a filtering window of size *3X3* if $\sum_{i=1}^{5} d^{(t)}(i)\geq 25$. The output of the detector is represented by a binary flag image {f(I, j)}, where f(i, j) = 1 indicates that the pixel $x(i,j)$ is noisy; for noiseless pixel, f(i, j) = 0. For the noise percentage of more than 40%, a bigger window of size *5 X 5* is used and the central pixel $x(i,j)$ is considered noisy if $\sum_{i=1}^{13} d^{(t)}(i)\geq 35$.

B. Filtering

For filtering the image, a weighted median filter with *3X3* window $W^{(x)}(i,j)$ is employed. The weight of a pixel is decided on the basis of standard deviation in four pixel directions (vertical, horizontal and two diagonals) as in [8]. Let *S* denote the set of pixels in the direction with minimum standard deviation. Accordingly, the noisy pixel is restored as

$$m(i,j)=median\{w_{m,n}\Diamond x(m,n)\};$$

$$m=i-1,i,i+1; n=j-1,j,j+1\cdots\cdots(5)$$

Where the weight $w_{m,n}$

$$=\begin{cases}2, if \rightarrow x(m,n)\in S\\ 1, otherwise\end{cases}$$

And the operator $\Diamond$ denotes repetition operation. The output of the filter is expressed

$$y(i,j)=\alpha_{i,j}x(i,j)+(1-\alpha_{i,j})m(i,j)\cdots\cdots(6)$$

$$where\ \alpha_{i,j}=\begin{cases}0, if\ f(i,j)=0\\ 1, if\ f(i,j)=0\end{cases}\cdots\cdots(7)$$

III. Results

In this section, restoration, noise detection capability of IID and the visual performances are evaluated and compared with number of existing median-based filters used to remove random-valued impulse noise. The standard gray-scale test images used in our experiments have distinctly different features. These images are “Lena”, “Peppers”, and “Boat”, each of size 512× 512. Commonly, most authors use the peak signal-to-noise ratio (PSNR) to quantify the restoration results. To complete comparisons, authors of [9] compute the number of missed noisy pixels and the number of noise-free pixels that are identified as noisy to show the efficiency of their method. In the same aim, we will present such results in following sub-Sections. All the reference filters are implemented in “MATLAB”

A. Restoration performance measurements

Restoration performances are evaluated quantitatively by using PSNR, which are defined as in [3]. We compare IID to other well known median-based filters, which include the standard median SM [1] (with a 3 ×3 filtering window if noise percentage P< 30% , and a 5 ×5 window otherwise), CWM filter [5] (W=3), SWM filter [6] (T=30),TSM filter [7] (T=20), MSWM filter[10] (Ti=50 ,and Tx =2), ATMA filter [8] (S=2 ,T=12 ,N=4 ,Wt=5,wu=30 , and iteration number =2 to4), DWM filter [9] (a 5×5 filtering window, To=512, and iteration number = 5 to 10),and ASWM [12] filter, we have ,δ=0.1 ,ε=0.01 and iteration number =3 to10. For IID filter, we have a 3×3 filtering window and the constant C of (3) is initialized as C=5 and varied as C=C+ t where t=10, 15,20,25,30. For all tested methods, a 3×3 filtering window is used, unless mentioned otherwise. Fig. 1 shows the performances of IID and other considered median based filters for “Lena” image in term of PSNR for random valued impulse noise with different noise densities. Fig. 2 shows the output images of various filtering methods considered in the study for 50% noise density. It can be seen that the proposed method successfully preserves the details in the image while removing the noise.

Table 1: PSNR of different schemes at 20% of noise on different images

Method	IMAGES		
	Lena	Boat	Pepper
S M	32.7	31.0	32.1
CWM	29.5	28.8	29.1
SWM	35.1	34.2	35.0
TSM	33.7	32.0	33.4
MSWM	33.6	33.1	33.6
ATMA	35.0	32.9	33.8
DWM	24.1	22.7	23.1
ASWM	35.1	34.2	34.8
I I D	36.16	35.2	36.0

Table 2: PSNR of different schemes at 50% of noise on different images

Method	IMAGES		
	Lena	Boat	Pepper
S M	17.7	17.2	17.4
CWM	16.7	11.5	11.5
SWM	27.2	25.6	26.3
TSM	17.4	17.0	17.2
MSWM	24.3	23.7	24.3
ATMA	18.4	18.0	18.0
DWM	17.2	16.8	17.0
ASWM	26.4	25.7	26.0
I I D	29.3	27.6	28.1

The noise density in the images is varied from 20% to 80%.The PSNR resulting from various experiments is shown in Table 1 and for “Lena”, “Boat”, and “Peppers” images, respectively. From these tables, it can be easily observed that the IID outperforms over other filtering schemes at all noise levels.

The MAE resulting from various experiments with 20% noise densities are shown in Table 3 for “Lena”, “Boat”, and “Peppers” images, respectively. From this table, it can be easily observed that the IID outperforms over other filtering schemes at all noise levels.

Table 3: MAE of different schemes at 20% of noise on different images

Method	IMAGES		
	Lena	Boat	Pepper
S M	3.5	5.4	4.04
CWM	3.4	4.7	3.8
SWM	1.5	2.2	2.4
TSM	4.4	5.1	4.5
MSWM	2.8	3.2	3.3
ATMA	1.8	2.3	2.0
DWM	3.0	3.6	3.7
ASWM	2.5	2.8	2.9
I I D	1.1	2.0	2.1

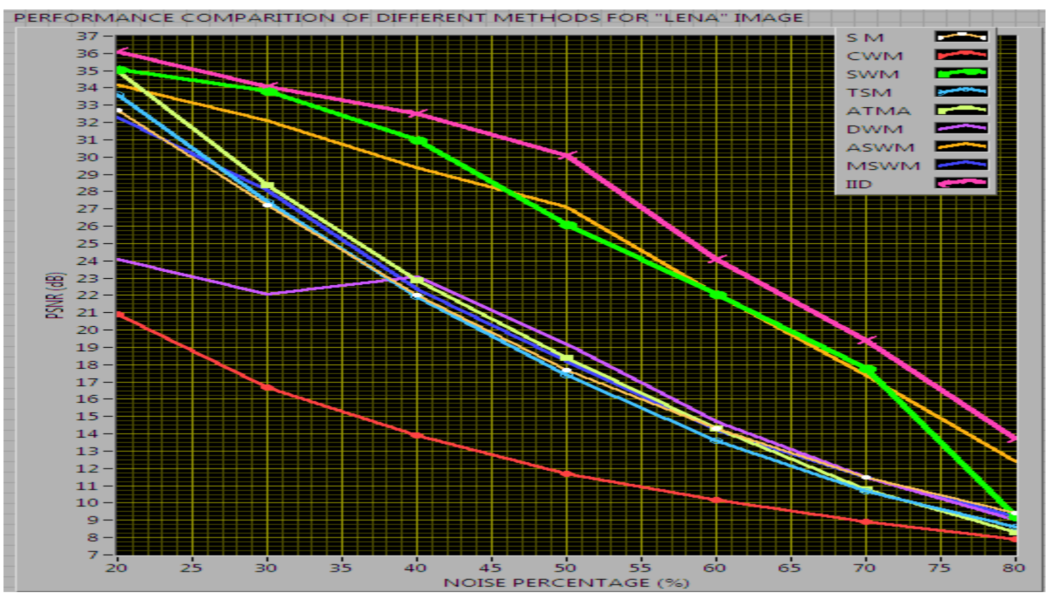


Figure 1: The performances of IID and other median based filters for “Lena” image in term of PSNR.

B. Noise detection

performance measurements Here, we compare IID method with five recently proposed methods. Table 4 lists the number of missed noisy pixels. In tables “Miss” term means a noisy pixel which is not detected as noise and “False” term means a noise free pixel detected as noise. For random-valued impulse noise, the noisy pixel values may not be so different from those of their neighbors.

Therefore it is more likely for a noise detector to miss a noisy pixel or detect a noise-free pixel as noise [9,11]. A good noise detector should be able to identify most of the noisy pixels. Its false alarm rate should be as small as possible. Results for IID are of high quality. IID can still distinguish most of the noisy pixels, even when the noise level is as high as 60%.

Table 4: Noise detection performance comparison results for "Lena" Image.

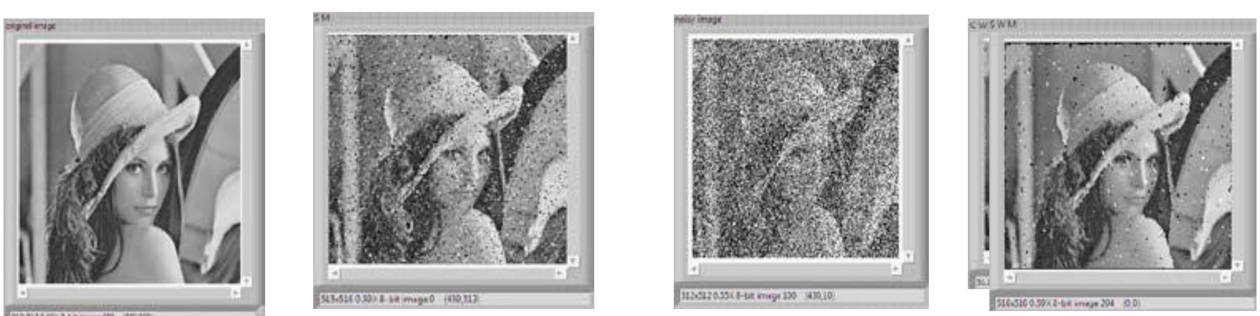
"LENA" Image						
Methods	10%		20%		30%	
	Miss	False	Miss	False	Miss	False
SWM	2532	2439	5084	3030	6869	3739
TSM	2515	1855	5037	2510	6763	2628
ATMA	2350	4916	4667	5502	6295	6337
DWM	2562	1364	5368	2901	7691	5061
ASWM	1594	1279	3019	4362	4083	4227
IID	1084	1103	2712	3896	3912	3989

Table contd…

Methods	40%		50%		60%	
	Miss	False	Miss	False	Miss	False
SWM	8333	4796	9484	6406	12612	9486
TSM	8167	3380	9190	4514	11612	9547
ATMA	7469	7953	7922	10551	7577	14582
DWM	9567	7507	11035	7342	8084	11526
ASWM	4180	4735	4735	8613	4840	9453
IID	4012	4586	4658	7625	4690	5623

C. Visual Performances

As a final illustration and in order to compare the methods subjectively, we give in Fig. 2, the "LENA" image with a 50% random valued impulse noise restored by various methods. IID exhibit excellent psycho-visual performances compared to other methods. Especially, the sketches of the LENA are well restored using IID. This result is of high importance for impulse noise removal.



(a)Original image (b) Noisy image (c) S M (d) C W M

(f) T S M (g) M S W M (h) A T M A

(i)DWM (j) A S W M (k) I I D

Fig. 2: (a to k), Restoration performance comparison on the "LENA" image degraded by 50% random-value impulsive noise.

IV. Conclusion

In this paper, an efficient noise detection scheme to remove random-valued impulse noise from images is presented. The detection of noisy pixels is based on a nonlinear function that progressively increases the gray level separation between noisy and noise-free pixels. The performance of the proposed scheme has been compared with many existing techniques. The efficiency of the proposed method is demonstrated by extensive simulations. From the experimental results, we can analyze that the IID restored the noisy image well in edges, contrast & exhibit better performance over several other methods. IID has shown high noise detection ability. Extensive simulations results indicate that IID performs significantly better than many other existing techniques. In addition, psycho visual results are of high quality. Finally, IID will be used as pre processing to remove random valued impulse noise.

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