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Second order difference based detection and directional weighted median filter for removal of random valued impulsive noise

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Abstract

The proposed approach of removal of random valued impulsive noise from images works in two phases. The first phase detects contaminated pixels and the second phase filters only those pixels keeping others intact. The detection scheme utilizes second order difference of pixels in a test window and the filtering scheme is a variation median filter based on the edge information. The proposed scheme is simulated extensively on standard images and comparison with existing schemes reveal that our scheme outperforms them in terms of Peak Signal to Noise Ratio (PSNR), number of false detection and miss detection. The proposed scheme is also good at preserving finer details. Further, the computational complexity and number of iterations needed by the proposed scheme is less than the existing counterparts.

I. Introduction

Images are often corrupted with impulsive noise during acquisition and/or transmission. The nonlinear characteristics of impulsive noise lead to poor performance of standard linear filters. A number of nonlinear filtering schemes have been reported in the literature [1], [2], [3], [4], [5], [6] to counter such noise. One of most widely used nonlinear filters is median filter. The simplicity in implementation and effective noise suppression capability has made the median filter popular. It is also computationally efficient. However, the restored result loses some desirable details of the original image as it is applied across the image and to all pixels irrespective of the location of noise. Impulsive noise with probability p can be modeled as

$$x(i,j) = \begin{cases} \eta(i,j) & \text{with probability } p \\ y(i,j) & \text{with probability } 1-p \end{cases} \tag{1}$$

where $x(i,j)$ and $y(i,j)$ denote the pixel values of noisy and original image at pixel location (i,j) and $\eta(i,j)$ is an identically distributed, independent random process with an arbitrarily underlying probability distribution.

For any image with a luminance range $[L_{\min}, L_{\max}]$, if $\eta(i,j) \in \{L_{\min}, L_{\max}\}$, the impulsive noise falls under the category of Salt & Pepper Noise. If $\eta(i,j)$ assumes any value in the range of $[L_{\min}, L_{\max}]$, it is termed as random valued impulsive noise (RVIN). Impulsive noise has the characteristic of contaminating only a certain percentage of image pixels leaving remaining pixels unchanged. Further, the gray values of corrupted pixels are significantly different from the gray values of their neighboring pixels. The primary concern in impulsive noise removal is to suppress the noise as well as to preserve the image details (edges).

Most of the reported schemes use two-stage process for removing RVIN namely detection followed by filtering. The median filter or its variation is used in the filtering stage with a detector applied a priori. Some of the reported schemes like signal-dependent rank order mean (SD-ROM) filter [1], multistate median (MSM) filter [6], adaptive center-weighted median (ACWM) filter [3] and the pixel-wise MAD (PWMAD) filter [5] have shown improved results.

In a recently reported scheme, directional weighted median (DWM) filter [7] is applied recursively for 8 to 10 iterations to the noisy image. This filter uses a new impulse detector, which is based on the differences between the current pixel and its neighbours aligned with four main directions. After impulse detection, it does not simply replace noisy pixels identified by outputs of median filter but continue to use the information of the four directions to weight the pixels in the window in order to preserve the details while removing noise. Even though results are encouraging at high noise densities, the high computational overhead discourages for real time implementations. In this paper, a similar scheme is proposed which utilizes a simple detector followed by weighted median filter. The proposed method with 3 iterations outperforms the DWM scheme with 10 iterations at low and medium noise cases with much less computational overhead.

Rest of the paper is organized as follows. Section II illustrates the proposed detection scheme. Section III highlights the filtering methodology. Simulation results and discussions are furnished in Section IV. Finally, Section V highlights the concluding remarks.

II. Proposed Impulse Detector

The proposed detection algorithm is based on the second order difference (SOD) among pixels in a test window to determine the noise status of the centre pixel. The SODs have a stronger response to fine details, such as thin lines and isolated points. For an isolated noise point, the SOD yields a value of larger magnitude. This property has been exploited in the proposed impulse detector.

Consider a 3×3 window W symmetrically surrounding the test pixel $x(i,j)$ as

$$W = \{x(i+s, j+t) | -1 \leq s, t \leq 1\} \tag{2}$$

Edges aligned with four main directions are captured by computing the SODs as in (3) with the directions shown in Fig. 1.

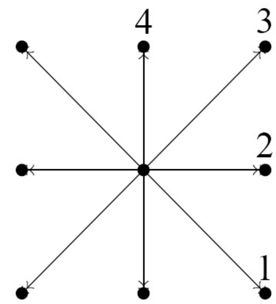

Fig. 1. Four directions for impulse detection

$$d_k = |x(i+u, j+v) + x(i-u, j-v) - 2x(i,j)| \tag{3}$$

$$\text{where, } (k,u,v) = \{(1,1,1),(2,0,1),(3,-1,1),(4,-1,0)\}$$

Then, the minimum of these four second-order-differences are used for impulse detection, which can be denoted as

$$\mathrm{d} = \min\{d_k : 1 \leq k \leq 4\} \tag{4}$$

A smaller value of d implies that the test pixel is noise-free and falls either on a flat region or on an edge. For a flat region noise-free pixel, all the four direction differences are small. When a noise-free pixel falls on an edge it yields smallest SOD along the edge. On the other hand a test pixel when noisy shall have large SOD in all directions resulting in a larger value of d.

III. Proposed Filter

Once the coordinate of an impulse is located the noisy pixel is replaced with an appropriate intensity value. This substitution is computed using a weighted median filter supported with four directional information. Let $S_k(i,j)$ denotes the gray level difference between the two neighboring pixels of $x(i,j)$ in the k^{th} direction $(1 \leq k \leq 4)$.

$$S_k(i,j) = |x(i+u, j+v) - x(i-u, j-v)| \tag{5}$$

$$\text{where, } (k,u,v) = \{(1,1,1),(2,0,1),(3,-1,1),(4,-1,0)\}$$

These four values of S_k signifies the closeness of the neighbouring pixels. Let D_k be the direction of minimum S_k, $(1 \leq k \leq 4)$. This shows that the pixels aligned along D_k are closest to each other and the center value should be close to them. Thus, these pixels are assigned with extra weight (w) while restoring the noisy pixels. If the test pixel $x(i,j)$ is found to be noisy, it is replaced with $r(i,j)$ that can be expressed as

$$r(i,j) = \text{median}\{W,\ w \diamond x_{D_k}\} \tag{6}$$

where, W is the window surrounding the test pixel as defined in (2), and x_{D_k} denotes the two neighboring pixels of $x(i,j)$ along the direction D_k. The symbol $\diamond$ is used as the repetition operator. This filtered pixel takes part in the noise detection process of subsequent windows making it a recursive process.

High accuracy of the proposed filter is ensured by recursively and iteratively applying the proposed scheme. Subsequent iterations use smaller threshold T as compared to the previous iterations in order to capture more noise. It has been observed from the simulations conducted on a variety of standard images that the set of threshold values $[T_1 \;\; T_2 \;\; T_3] = [35 \;\; 25 \;\; 18]$ yields satisfactory results.

IV. Simulation Results and Discussions

To validate the proposed scheme, simulations have been carried out on standard images like *Lena*, *Boat*, *Bridge* etc. The existing schemes are also simulated with the same set of images in the same environment. Both objective as well as subjective studies are performed by accumulating the results obtained from various schemes. The performance measures in terms of PSNR (dB) for *Lena* and *Bridge* images are shown in Table I and Table II respectively. It may be observed from these two tables that the proposed scheme outperforms its counterparts except the recently reported DWM filter which shows a slightly superior performance as compared to the proposed scheme beyond 40% noise densities.

Number of computations needed per single window detection as well as filtering between the proposed and DWM filter are shown in Table III. This clearly reveals that there exists a remarkable difference in computational overhead. To measure the subjective performance, the restored images by various filtering schemes are shown in Fig. 2 and 3 at 30% noise density. A closer look at the feathers and iris of the enlarged *Lena* image (Fig. 3) justifies that the proposed scheme is good at detail preservation.

TABLE I
Comparison of PSNR (dB) for *Lena* Image

Method	10%	20%	30%	40%	50%	60%
ACWM	34.47	32.44	30.40	27.86	25.66	22.51
PWMAD	34.86	30.58	25.94	22.41	19.42	17.08
DWM	35.15	33.81	32.43	30.64	29.14	26.57
Proposed	36.89	34.35	32.53	30.90	28.22	24.84

V. Conclusions

This paper proposes a novel impulsive noise removal scheme from images. The scheme works in two phases, namely impulse detection followed by filtering of contaminated pixels using a modified weighted median filter. The detection scheme utilizes a simple second order difference in different directions in a test window. While filtering, edge directions are found using simple method. Subsequently, edge direction pixels are given more weightage in filtering operation. This substantiates retrieval of the lost edges, which avoids blurring in restored images. Simulation results show the efficacy of the proposed scheme in terms of PSNR, false and miss detection and finer detail preservation. The low computational overhead makes the proposed scheme to be a potential candidate for real time applications.

References

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TABLE II
Comparison of PSNR (dB) for *Bridge* Image

Method	10%	20%	30%	40%	50%	60%
ACWM	25.89	25.14	23.99	22.61	20.88	19.09
PWMAD	25.98	25.22	22.91	20.27	17.86	15.77
DWM	26.02	26.50	24.87	24.09	23.08	21.41
Proposed	27.80	27.20	24.91	23.73	22.14	20.02

TABLE III
COMPUTATIONAL OVERHEAD BETWEEN THE PROPOSED AND THE DWM FILTER

Filter	Impulse Detection Phase			Filtering Phase		
	Window	Additions	Multiplications	Additions	Multiplications	Exponentiation
DWM	5×5	28	08	48	07	One square root
Proposed	3×3	08	04	42	01	00

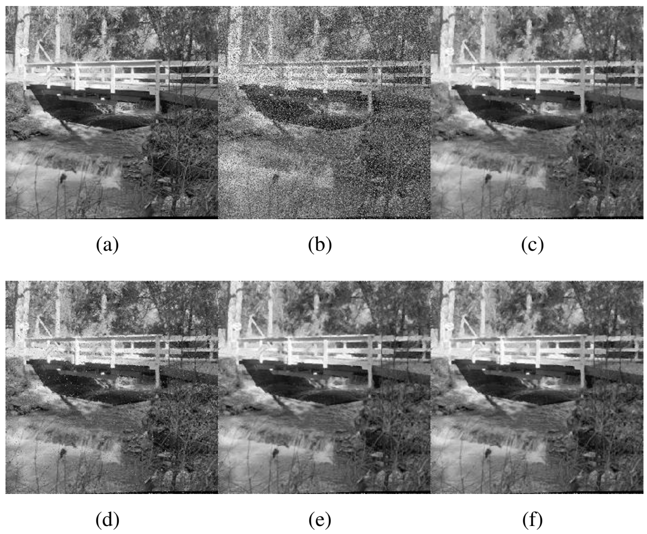

Fig. 2. Restored results of the *Bridge* image corrupted with 30% of RVIN (a) Original image, (b) Noisy image, (c) ACWMF, (d) PWMAD, (e) DWMF, (f) Proposed.

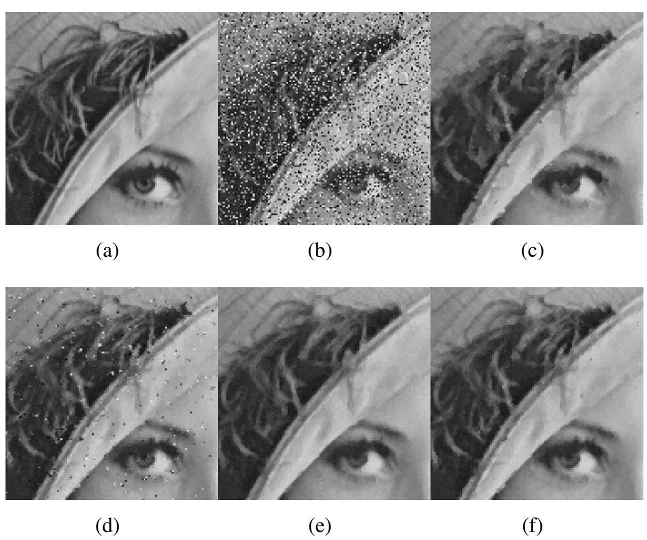

Fig. 3. Restored results of enlarged *Lena* image corrupted with 30% of RVIN (a) Original image, (b) Noisy image, (c) ACWMF, (d) PWMAD, (e) DWMF, (f) Proposed.