An Efficient Edge-Preserving Algorithm for Removal of Salt-and-Pepper Noise

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***Abstract*—In this letter, a novel algorithm for removing salt-and-pepper noise from corrupted images is presented. We employ an efficient impulse noise detector to detect the noisy pixels, and an edge-preserving filter to reconstruct the intensity values of noisy pixels. Extensive experimental results demonstrate that our method can obtain better performances in terms of both subjective and objective evaluations than those state-of-the-art impulse denoising techniques. Especially, the proposed method can preserve edges very well while removing impulse noise. Since our algorithm is algorithmically simple, it is very suitable to be applied to many real-time applications.**

***Index Terms*—Image denoising, image restoration, impulse noise, salt-and-pepper noise.**

I. Introduction

IMAGE and video signals might be corrupted by impulse noise in the process of signal acquisition and transmission, so an efficient denoising technique is necessary for various image applications [1]. Recently, many image denoising methods have been proposed to carry out the impulse noise suppression [2]–[16]. Some of them employ the standard median filter [2] or its modifications [3], [4] to implement the denoising process. However, these approaches [2]–[4] might blur the image since both noisy and noise-free pixels are modified. To avoid the damage on noise-free pixels, many image filters with an impulse detector are proposed in the literature [5]–[16]. The main advantage of these methods is that they employ an impulse detector to locate and filter the noisy pixels without processing the noise-free pixels.

Many recent denoising techniques [12]–[16] use a fixed-size local window for processing and perform image denoising simply and efficiently. In [12], a new impulse detector (NID) for switching median filter was proposed. NID used the minimum absolute value of four convolutions which are obtained by using one-dimensional Laplacian operators to detect noisy pixels. The differential rank impulse detector (DRID), presented in [13], implemented the impulse detector based on a comparison of signal samples within a narrow rank window by both rank and absolute value. In [14], a simple fuzzy impulse detector (SFID) was proposed to remove the impulse noise. An alpha-trimmed mean-based method (ATMBM) was presented in [15]. It used the alpha-trimmed mean in impulse detection and replaced the noisy pixel value by a linear combination of its original value and the median of its local window. In [16], a decision-based algorithm (DBA) was presented to remove the corrupted pixel by the median or by its neighboring pixel value according to the proposed decisions.

In [8], a two-phase scheme for salt-and-pepper noise removal is proposed. It identifies the noisy pixels with an adaptive median filter and then restores them by an edge-preserving method. Based on their idea, an efficient edge-preserving algorithm for impulse noise removal is proposed in this letter. We use a noise detector to detect the pixels corrupted by impulse noise. After detection, we employ an effective edge-preserving filter to preserve the edge features rather than reconstruct the noisy pixel values with standard median filter. The experimental results demonstrate that our method can obtain better performances in terms of both quantitative evaluation and visual quality than those state-of-the-art impulse denoising methods [12]–[16].

The rest of this letter is organized as follows. In Section II, the proposed algorithm is introduced. The implementation results and comparison are provided in Section III. The conclusions are presented in Section IV.

II. Proposed Algorithm

The noise considered in this letter is fixed-valued impulse noise, also called salt-and-pepper noise, with uniform distribution as practiced in [12]–[16]. The proposed algorithm is composed of two components: efficient impulse detector and edge-preserving filter. The former determines which pixels are corrupted by fixed-valued impulse noise. The latter reconstructs the noisy pixels by observing the spatial correlation and preserving the edges efficiently.

A. Efficient Impulse Detector

Let $p_{i,j}$ denote the current pixel at coordinate (i,j) and $y_{i,j}$ denote its pixel value. For each pixel in an image, we define a 3×3 window centered on it first. Let $W_{i,j}$ represent the set of pixels within a 3×3 window centered on $p_{i,j}$. Thus, it can be given as

$$W_{i,j} = \{p_{k,l} | i-1 \le k \le i+1,\ j-1 \le l \le j+1\}. \quad (1)$$

Assume that $MaxinW_{i,j}$ and $MininW_{i,j}$ mean the maximum and minimum gray-scale values in the current working window $W_{i,j}$, respectively, and let $Max_{i,j}$ and $Min_{i,j}$ mean the maximum and minimum gray-scale values in those previously processed windows from the first one $(W_{0,0})$ to the current one $(W_{i,j})$. The relationships between them are given as follows:

$$Max_{i,j} = \begin{cases} Max_{i,j-1}, & \text{if } Max_{i,j-1} \ge MaxinW_{i,j} \\ MaxinW_{i,j}, & \text{otherwise} \end{cases} \quad (2)$$

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$$Min_{i,j} = \begin{cases} Min_{i,j-1}, & \text{if } Min_{i,j-1} \leq MininW_{i,j} \\ MininW_{i,j}, & \text{otherwise.} \end{cases} \quad (3)$$

Generally, the value of a pixel corrupted by fixed-valued impulse noise will be located at one of the two ends in the interval of possible pixel values in the image [14]. Based on the idea, we define two variables, $N_{\max}$ and $N_{\min}$, for efficient impulse detection. They are given as

$$N_{\max} = \begin{cases} Max_{i,j}, & \text{if } Max_{i,j} = Max_{i,j-1} \\ 255, & \text{otherwise} \end{cases} \quad (4)$$

$$N_{\min} = \begin{cases} Min_{i,j}, & \text{if } Min_{i,j} = Min_{i,j-1} \\ 0, & \text{otherwise} \end{cases} \quad (5)$$

where $N_{\max}$ and $N_{\min}$ can be treated as the estimated intensity values of "salt" and "pepper" noises, respectively, in those previously processed pixels ranging from $p_{0,0}$ to $p_{i,j}$. If $Max_{i,j}$ is equal to $Max_{i,j-1}$, it is very possible that the intensity value of "salt" noise in current image is identified. Hence, we set $N_{\max}$ to $Max_{i,j}$. On the contrary, if $Max_{i,j}$ is not equal to $Max_{i,j-1}$, we cannot conclude that the value of $Max_{i,j}$ is the intensity value of "salt" noise. In this case, we set $N_{\max}$ to 255. Similarly, the estimated intensity value of "pepper" noise $N_{\min}$ can be determined.

Finally, the impulse detection function is given as (6) at the bottom of the page. If the intensity value of current pixel is equal to $N_{\max}$ or $N_{\min}$, the current pixel is treated as a noisy pixel and the edge-preserving filter mentioned later is employed to reconstruct its intensity value. If not, the current pixel is treated as a noise-free pixel and the original intensity value is outputted.

B. Edge-Preserving Image Filter

The proposed edge-preserving image filter adopts a directional correlation-dependent filtering technique based on observing the sample correlations of six different directions. For each noisy pixel, the image filter detects edges in six directions first and estimates the intensity value of the pixel accordingly. For simpler representation, let a, b, c, d, e, f, g, and h represent those intensity values of pixels, $p_{i-1,j-1}$, $p_{i-1,j}$, $p_{i-1,j+1}$, $p_{i,j-1}$, $p_{i,j+1}$, $p_{i+1,j-1}$, $p_{i+1,j}$, and $p_{i+1,j+1}$, respectively, around the current pixel $p_{i,j}$ as shown in Fig. 1. The detailed steps of our edge-preserving image filter are described as follows.

1) Find the six directional differences around the pixel $p_{i,j}$ in $W_{i,j}$ in (7) at the bottom of the page.

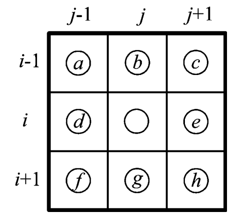

Fig. 1. Those pixels around the current pixel $p_{i,j}$.

2) Check whether the four pixels to be denoised later (e, f, g, and h) are equal to $N_{\max}$ or $N_{\min}$, respectively. If yes, the pixel might be corrupted, and thus we do not consider the directional differences containing it by setting those differences to 512.

3) Determine whether D_1, D_2, D_4, and D_5 are equal to 512, respectively. If at least one of D_1 and D_2 is equal to 512, and $p_{i+1,j+1}$ is noise-free, we consider an extra directional difference D_7 to improve image quality. Furthermore, if at least one of D_4 and D_5 is equal to 512, and $p_{i+1,j-1}$ is noise-free, we add another directional difference D_8. Both of them are defined as follows:

$$\begin{cases} D_7 = |a-h| \times 2 \\ D_8 = |c-f| \times 2. \end{cases} \quad (8)$$

4) Find the minimum value among those directional differences and denote it as $D_{\min}$. The minimum directional difference has the strongest correlation and probably has an edge in its direction. Hence, the reconstructed value of the corrupted pixel $p_{i,j}$ is estimated as follows:

$$y_{i,j} = \begin{cases} \frac{(a+d+e+h)}{4}, & \text{if } D_{\min} = D_1 \\ \frac{(a+b+g+h)}{4}, & \text{if } D_{\min} = D_2 \\ \frac{(b+g)}{2}, & \text{if } D_{\min} = D_3 \\ \frac{(b+c+f+g)}{4}, & \text{if } D_{\min} = D_4 \\ \frac{(c+d+e+f)}{4}, & \text{if } D_{\min} = D_5 \\ \frac{(d+e)}{2}, & \text{if } D_{\min} = D_6 \\ \frac{(a+h)}{2}, & \text{if } D_{\min} = D_7 \\ \frac{(c+f)}{2}, & \text{if } D_{\min} = D_8. \end{cases} \quad (9)$$

However, there is an exception for step 4. If $D_{\min}$ is equal to 512, it means that $p_{i,j+1}$, $p_{i+1,j-1}$, $p_{i+1,j}$, and $p_{i+1,j+1}$ are all corrupted. In this condition, no edge is considered. Here, we employ the two previously denoised pixels, $p_{i-1,j+1}$ and

$$p_{i,j} \text{ is a} \begin{cases} \text{noisy pixel}, & \text{if } (y_{i,j} = N_{\max}) \text{ or } (y_{i,j} = N_{\min}) \\ \text{noise} - \text{free pixel}, & \text{otherwise} \end{cases} \quad (6)$$

$$\begin{cases} D_1 = |d-h| + |a-e|, \ D_2 = |a-g| + |b-h|, \ D_3 = |b-g| \times 2 \\ D_4 = |b-f| + |c-g|, \ D_5 = |c-d| + |e-f|, \ D_6 = |d-e| \times 2 \end{cases} \quad (7)$$

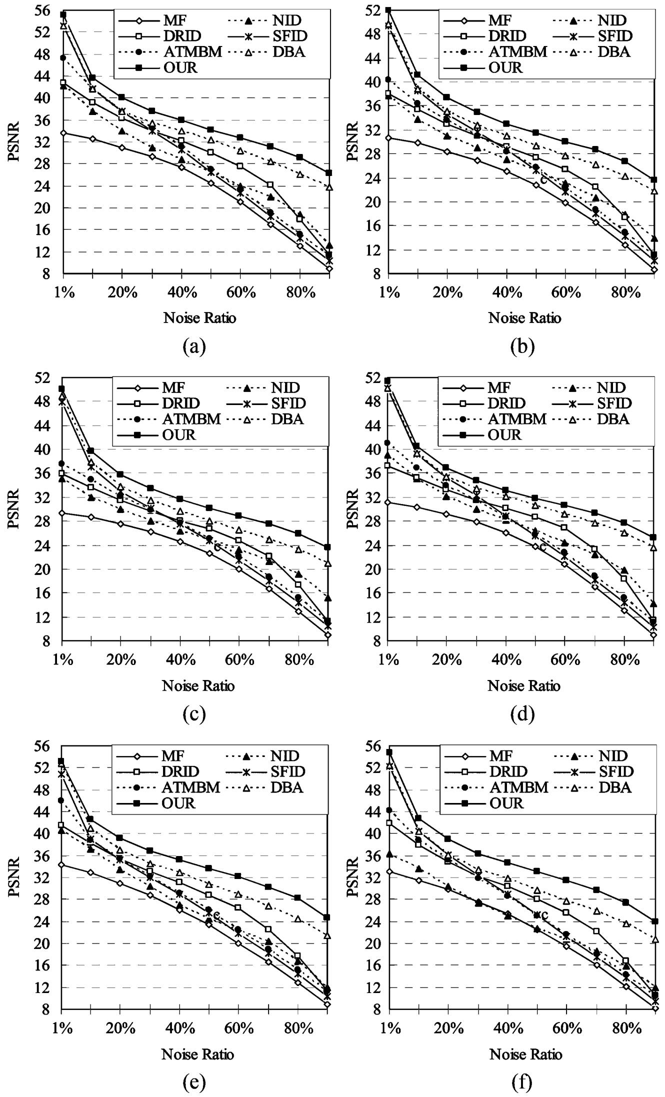

Fig. 2. Comparison of restoration results in PSNR for the images: (a) Lena, (b) Boat, (c) Couple, (d) Goldhill, (e) Peppers, and (f) Plane corrupted with various ratios of fixed-valued impulse noise.

TABLE I
COMPARISONS OF RESTORATION RESULTS IN PSNR (dB) FOR IMAGE "LENA"

	1%	10%	20%	30%	40%	50%	60%	70%	80%	90%
Median Filter [2]	33.63	32.58	31.00	29.27	27.40	24.41	21.06	17.03	12.95	8.95
NID [12]	42.25	37.46	34.03	31.00	28.72	26.42	23.98	21.95	18.72	13.18
DRID [13]	42.73	39.11	36.22	33.92	32.15	29.94	27.53	24.07	17.84	11.33
SFID [14]	53.07	41.66	37.55	33.97	30.50	26.46	22.61	18.43	14.53	10.38
ATMBM [15]	47.28	41.56	37.42	34.47	31.10	27.03	23.21	19.09	15.21	11.16
DBA [16]	53.07	41.67	37.49	35.40	34.04	32.31	30.47	28.34	26.10	23.72
Our method	**55.04**	**43.66**	**40.05**	**37.62**	**35.91**	**34.22**	**32.76**	**31.15**	**29.20**	**26.25**

$p_{i,j-1}$, and take the mean of them as the reconstructed value. In this case, $y_{i,j} = (c+d)/2$. Obviously, the proposed filter has a simple computation structure.

III. EXPERIMENTAL RESULTS

In this section, we compare our method with a number of existing denoising approaches for removal of fixed-valued impulse noise. To verify the characteristics and performances of various denoising algorithms, a variety of simulations are carried out on the six well-known 512×512 8-bit gray-scale test images:

TABLE II
COMPARISONS OF RESTORATION RESULTS IN PSNR (dB) FOR SIX REFERENCE IMAGES CORRUPTED BY 20% FIXED-VALUED IMPULSE NOISE

	Lena	Boat	Couple	Goldhill	Peppers	Plane
Median Filter [2]	31.00	28.44	27.56	29.19	31.00	29.80
NID [12]	34.03	31.05	29.95	32.18	33.37	30.32
DRID [13]	36.22	33.01	31.49	33.22	35.39	34.87
SFID [14]	37.55	34.67	32.97	35.21	35.26	36.06
ATMBM [15]	37.42	33.34	32.21	33.87	35.32	35.24
DBA [16]	37.49	35.02	33.78	35.41	36.94	36.16
Our method	**40.05**	**37.33**	**35.71**	**36.91**	**39.12**	**38.94**

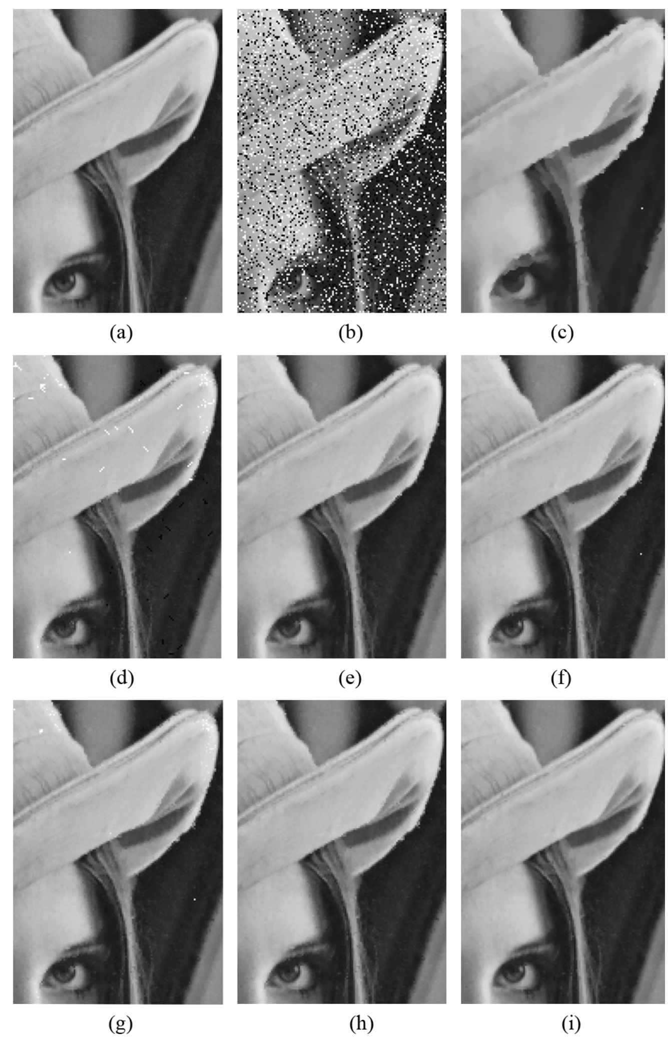

Fig. 3. Restoration results of different methods in restoring corrupted image "Lena." (a) Original noise-free image, (b) corrupted image with 20% impulse noise, (c) median filter, (d) NID, (e) DRID, (f) SFID, (g) ATMBM, (h) DBA, and (i) our method.

Lena, Boat, Couple, Goldhill, Peppers, and Plane. In the simulations, images are corrupted by salt-and-pepper noise, where 255 represents the "salt" noise and 0 represents the "pepper" noise with equal probability. A wide range of noise ratios varied from 1%, 10% to 90% with increments of 10% are tested. Totally, seven recent denoising methods are compared in terms of objective testing (quantitative evaluation) and subjective testing (visual quality): 1) standard median filter of size 3×3 (MF) [2], 2) new impulse detector (NID) [12], 3) differential rank impulse detector (DRID) [13], 4) simple fuzzy impulse detector (SFID)

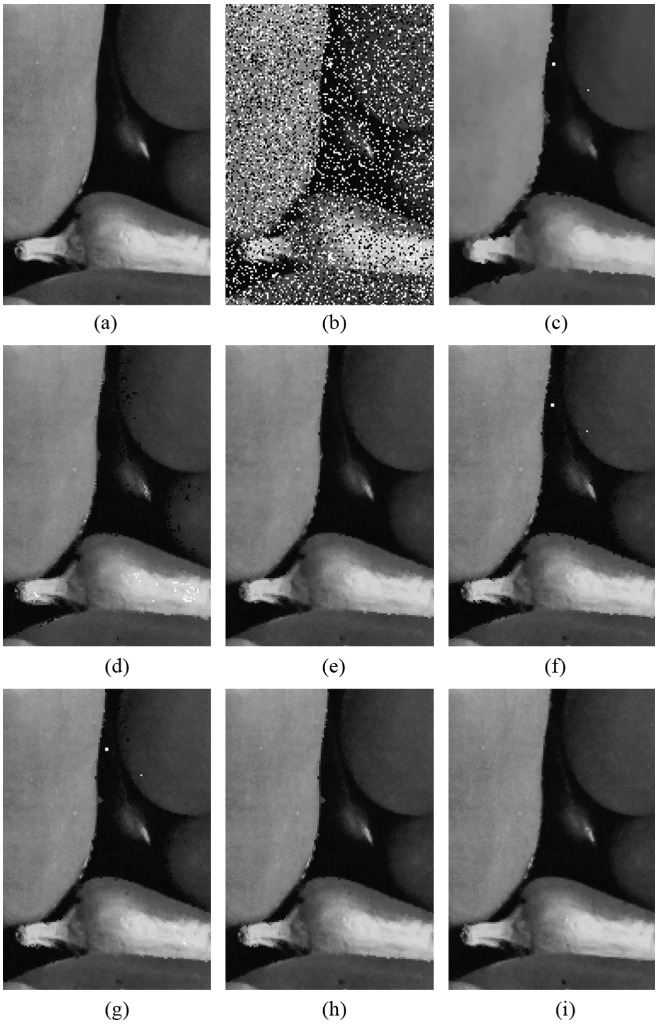

Fig. 4. Restoration results of different methods in restoring corrupted image "Peppers." (a) Original noise-free image, (b) corrupted image with 30% impulse noise, (c) median filter, (d) NID, (e) DRID, (f) SFID, (g) ATMBM, (h) DBA, and (i) our method.

[14], 5) alpha-trimmed mean-based method (ATMBM) [15], 6) decision-based algorithm (DBA) [16], and 7) our method. The parameters or thresholds of previous methods [12]–[16] are set as suggested.

We employ the peak signal-to-noise ratio (PSNR) to illustrate the quantitative quality of the reconstructed images for various methods. Table I lists the restoration results in PSNR (dB) of different approaches for image "Lena" corrupted by fixed-valued impulse noise with various noise ratios. It is easy to see that our method provides the best results in PSNR. In Table II, we compare the restoration results in PSNR (dB) of our method with other denoising methods for six reference images corrupted by 20% fixed-valued impulse noise. Obviously, our approach performs significantly better than other methods. The comparison of restoration results in PSNR for the reference images corrupted with various impulse noise ratios are shown in Fig. 2. Apparently, the performances of our method are always the best. Certainly, the exact degree of improvement is dependent on the content of different images processed.

In order to explore the visual quality, we show the reconstructed images of different denoising methods in restoring 20% corrupted image "Lena" in Fig. 3, and in restoring 30% corrupted image "Peppers" in Fig. 4, respectively. The median filter brings out blurry restored images and other methods are not good enough with regard to edge preservation. In contrast, our method can remove noise efficiently while preserving edges very well, and it can produce visually pleasing images.

IV. Conclusion

A new denoising algorithm for removing salt-and-pepper noise is proposed in this letter. It can detect the impulse noise efficiently while preserving the edges very well. The simulation results demonstrate that our approach performs much better than other existing techniques in terms of both quantitative evaluation and visual quality. Particularly, it removes the noise from corrupted images efficiently and requires no previous training.

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