An Efficient Detail-Preserving Approach for Removing Impulse Noise in Images

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***Abstract*—In this letter, we present a new efficient algorithm for the removal of impulse noise from corrupted images while preserving image details. The algorithm is based on the alpha-trimmed mean, which is a special case of the order-statistics filter. However, unlike some of the previous techniques involving order-statistics filters, the proposed method uses the alpha-trimmed mean only in impulse noise detection instead of pixel value estimation. Once a noisy pixel is identified, its value is replaced by a linear combination of its original value and the median of its local window. Extensive computer simulations indicate that our algorithm provides a significant improvement over many other existing techniques.**

***Index Terms*—Image restoration, impulse noise, median filter, noise detection.**

I. Introduction

THE acquisition or transmission of digital images through sensors or communication channels is often interfered by impulse noise [1]. It is very important to eliminate noise in the images before subsequent processing, such as image segmentation, object recognition, and edge detection. A large number of techniques [2]–[16] have been proposed to remove impulse noise from corrupted images, for example, rank conditioned rank selection filter [4], various adaptive median filters [2]–[7], [10], fuzzy technique [9], [12], adaptive center weighted median filter [15], and Laplacian operator [16], etc. In addition, some methods, such as those in [6], are based on previous training. Many existing methods use an impulse detector to determine whether a pixel should be modified. Then, the filtering process is applied only to the identified noisy pixels. This technique, called switching strategy, has been shown to be simple and yet more effective than uniformly applied methods, such as median filter [2], [10].

In this letter, a new efficient approach, which is based on alpha-trimmed means, is proposed to remove impulse noise from corrupted images while preserving image details. It is well known that the alpha-trimmed mean [17] is a special case of the order-statistics filter [18]. The difference between our approach and those proposed in [17] and [18] is that our algorithm uses the alpha-trimmed mean in impulse noise detection instead of pixel value estimation. Also, it applies the filtering process to only the identified noisy pixels instead of all image pixels. Extensive experimental results show that our algorithm performs significantly better than many other well-known techniques.

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II. Our Proposed Alpha-Trimmed Mean-Based Approach

It is well known that sample mean might be inadequate in high-noise situations to represent the main body of the data but rather will be biased toward the "outliers" [17]. Since a noisy pixel is usually located near one of the two ends in the sorted sample [1], a robust statistical estimator, for example, *trimmed mean*, is more intuitively appealing than sample mean [17].

The proposed algorithm consists of three steps: impulse noise detection, refinement, and impulse noise cancellation, which replaces the values of identified noisy pixels with estimated ones.

A. Impulse Noise Detection

Let I denote the corrupted, noisy image of size $l_1 \times l_2$, and x_{ij} is its pixel value at position (i,j), i.e., $I = \{x_{ij} : 1 \le i \le l_1, 1 \le j \le l_2\}$. Let $W_{ij}(I)$ denote the window of size $(2L_d+1) \times (2L_d+1)$ centered about x_{ij}, i.e., $W_{ij}(I) = \{x_{i-u,j-v} | -L_d \le u,v \le L_d\}$. The alpha-trimmed mean $\overline{M}_{ij}^{\alpha}(I)$ of the pixel values within window $W_{ij}(I)$ is defined as

$$\overline{M}_{ij}^{\alpha}(I) = \frac{1}{t - 2 * \lfloor \alpha t \rfloor} \sum_{i=\lfloor \alpha t \rfloor + 1}^{t - \lfloor \alpha t \rfloor} X_{(i)} \tag{1}$$

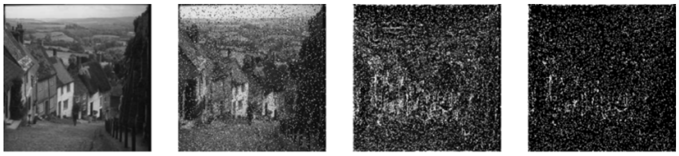
where $t = (2L_d+1)^2$, α is the trimming parameter that assumes values between 0 and 0.5, $\lfloor \cdot \rfloor$ is the floor function, and $X_{(i)}$ represents the ith data item in the increasingly ordered samples of $W_{ij}(I)$, i.e., $X_{(1)} \le X_{(2)} \le \cdots \le X_{(t)}$ [17]. That is,

$$X_{(i)} = i\text{th smallest } (W_{ij}(I)).$$

Since the alpha-trimmed mean $\overline{M}_{ij}^{\alpha}(I)$, with appropriately chosen α, represents approximately the average of the noise-free pixel values within window $W_{ij}(I)$, the absolute difference r_{ij} between x_{ij} and $\overline{M}_{ij}^{\alpha}(I)$

$$r_{ij} = \left| x_{ij} - \overline{M}_{ij}^{\alpha}(I) \right| \tag{2}$$

should be relatively large for noisy pixels and small for good, noise-free pixels. Let $\mathcal{R}^{(0)} = \{r_{ij} : 1 \le i \le l_1, 1 \le j \le l_2\}$, and it is called the *residue* image of I. We plot the residue image $\mathcal{R}^{(0)}$ for image *Goldhill* of size 256 × 256 in Fig. 1(c), along with the original image [see Fig. 1(a)] of *Goldhill* and the noisy image I [see Fig. 1(b)] of *Goldhill* corrupted by 10% fixed-valued impulse noise, where the impulses take on the values of 0 or 255 with equal probabilities [6]. For simplicity, in the experiment, we set $L_d = 1$ and $\alpha = 0.35$. From Fig. 1(c), it is clear that the residue image $\mathcal{R}^{(0)}$ contains not only noisy pixels but also some image details such as the sketches of the houses. If



(a) (b) (c) (d)

Fig. 1. Residue images for *Goldhill*. (a) Original image *Goldhill*. (b) *Goldhill* corrupted by 10% fixed-valued impulse noise, i.e., I. (c) $\mathcal{R}^{(0)}$. (d) $\mathcal{R}^{(1)}$. The pixel values in the residue images (c) and (d) are amplified for better visualization.

we compare r_{ij} with a threshold value to determine whether or not the pixel x_{ij} is noisy, then it will detect many image details as noisy as well. In order to improve the impulse noise detection accuracy, ideally, we need to remove all the image details from the residue image $\mathcal{R}^{(0)}$. Next, we propose a simple and efficient method to remove image details from $\mathcal{R}^{(0)}$.

Our method is based on the following observations. First, when the pixel x_{ij} is an impulse, it takes a value substantially larger than or smaller than those of its neighbors. Second, when the pixel x_{ij} is a noise-free pixel, which could belong to a flat region, an edge, or even a thin line, its value will be very similar to those of some of its neighbors. Therefore, we can detect image details from noisy pixels by counting the number of pixels whose values are similar to that of x_{ij} in its local window $W_{ij}(I)$. For $x_{i-u,j-v} \in W_{ij}(I)$ and $(u,v) \neq (0,0)$, we define

$$\delta_{i-u,j-v} = \begin{cases} 1, & |x_{i-u,j-v} - x_{ij}| < T \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

where T is a predetermined parameter. $\delta_{i-u,j-v} = 1$ indicates that the pixel $x_{i-u,j-v}$ is similar to the pixel x_{ij} in intensity. Also, let ξ_{ij} denote the total number of neighboring pixels in the window $W_{ij}(I)$ that are similar to the pixel x_{ij} in intensity. That is

$$\xi_{ij} = \sum_{-L_d \le u,v \le L_d, (u,v)\neq(0,0)} \delta_{i-u,j-v}. \tag{4}$$

Next, define φ_{ij} as

$$\varphi_{ij} = \begin{cases} 0, & \xi_{ij} \ge N \\ 1, & \text{otherwise} \end{cases} \tag{5}$$

where N is a predetermined parameter. $\varphi_{ij} = 0$ indicates that most likely x_{ij} is a noise-free pixel instead of an impulse because it has at least N similar neighboring pixels in the window $W_{ij}(I)$. Let $\mathcal{R}^{(1)} = \{r_{ij} * \varphi_{ij} : 1 \le i \le l_1, 1 \le j \le l_2\}$. It is clear that

$$r_{ij} * \varphi_{ij} = \begin{cases} 0, & \varphi_{ij} = 0 \\ r_{ij}, & \varphi_{ij} = 1. \end{cases} \tag{6}$$

Therefore, $\mathcal{R}^{(1)}$ retains the impulse noises in $\mathcal{R}^{(0)}$ while removing most of the image details, as shown in Fig. 1(d). From Fig. 1(d), it is clear that most image details disappear while the noise remains, thus improving the impulse noise detection accuracy in the subsequent steps. This is indeed very important for the good performance of our algorithm, as will be shown later.

Since impulse noises can be detected more accurately from the residue image $\mathcal{R}^{(1)}$, next, we apply a fuzzy impulse detection technique to give each pixel a fuzzy flag indicating how much it looks like an impulse. The more it looks like a damaged pixel, the more it is modified later. This technique is very efficient in removing impulse noise, especially random-valued impulse noise where the impulse values are uniformly distributed within [0, 255], as will be shown later. The following two-parameter membership function, similar to that in [9], is used to generate a fuzzy flag n_{ij} for each pixel x_{ij} in the noisy image I:

$$n_{ij} = \begin{cases} 1, & r_{ij} * \varphi_{ij} \ge W_u \\ \frac{r_{ij}*\varphi_{ij} - W_l}{W_u - W_l}, & W_l \le r_{ij} * \varphi_{ij} < W_u \\ 0, & r_{ij} * \varphi_{ij} < W_l \end{cases} \tag{7}$$

where W_l and W_u are two predetermined parameters. n_{ij} can be used to measure how much the pixel is corrupted.

B. Refinement

It is well known that a noisy pixel is usually located near one of the two ends in the ordered samples of $W_{ij}(I)$. In other words, if a pixel x_{ij} is not located near one of the two ends in the ordered samples, then most likely, it is not a noisy pixel. Based on this observation, we can refine the fuzzy flag n_{ij} as follows:

$$n_{ij} = \begin{cases} 0, & \texttt{if } X_{(s)} < x_{ij} < X_{(t-s+1)} \\ n_{ij}, & \texttt{otherwise} \end{cases} \tag{8}$$

where s is constant, and $1 \le s \le (t-1)/2$.

C. Impulse Noise Cancellation

After we calculate the membership function n_{ij} for each pixel x_{ij}, the pixel value of x_{ij} is replaced by a linear combination of the median $m_{ij}(I)$ of $W_{ij}(I)$, i.e., $m_{ij}(I) = \texttt{median}(W_{ij}(I))$, and its original value x_{ij}. That is

$$y_{ij} = n_{ij} \times m_{ij}(I) + (1 - n_{ij}) \times x_{ij} \tag{9}$$

where y_{ij} is the restored value of x_{ij}.

III. Experimental Results

In this section, the proposed algorithm is evaluated and compared with many other existing techniques. Extensive experiments are conducted on a variety of standard gray-scale test images with distinctly different features and different sizes, including *Lena*, *Bridge*, and *Goldhill*. For simplicity, we set $L_d = 1$ and $\alpha = 0.35$ in our computer simulations. For fixed-valued impulse noise, $s = 1, T = 30, N = 4, W_l = 20$, and $W_u = 40$, while for random-valued impulse noise, $s = 2, T = 12, N = 4, W_l = 5$, and $W_u = 30$. The proposed algorithm is implemented recursively. That is, the modified pixel values are immediately used in process of the following pixels. In order to further improve the restoration results, the proposed algorithm is applied iteratively. Usually, the best restoration results can be obtained after two to four iterations. Peak signal-to-noise ratio (PSNR) is used to give quantitative performance measures as in [2]–[16], [20], and [21].

TABLE I
COMPARATIVE RESULTS IN PSNR FOR IMAGE *Lena* OF SIZE 512 × 512 CORRUPTED BY 20% FIXED-VALUED IMPULSE NOISE AND RANDOM-VALUED IMPULSE NOISE, RESPECTIVELY

Algorithm	Fixed-valued Impulses	Random-valued Impulses
Median filter	28.57	29.76
CWM [3]	30.39	32.42
SWM-I [2]	31.97	31.34
SWM-II [2]	29.96	32.04
RCRS filter [4]	31.36	30.78
AMF [5]	30.57	31.18
TSM filter [10]	31.84	34.13
DBM filter [11]	35.12	31.66
Fuzzy filter [12]	30.75	28.66
SD-ROM [6]	35.70	33.37
LRC method [13]	36.95	33.43
FM [8]	34.83	34.32
Fuzzy approach [9]	36.47	33.78
ACWMF [15]	36.54	34.98
Our approach	**37.45**	**35.22**

First, the performance of our proposed method in impulse noise suppression is compared with those of many other well-known algorithms, which include the standard median filter of size 3 × 3, the center-weighted median (CWM) filter of size 3 × 3 [3], the median filter with adaptive length (AMF) [5], the median filter based on fuzzy rules (FM) [8], the SD-ROM approach [6], and the adaptive center-weighted median filter (ACWMF) in [15]. For the CWM filter, center weights are appropriately tuned to obtain better performance for different noisy images. Unless otherwise mentioned, the SD-ROM approach used inside training set with $M = 1296$, as defined in [6]. The test image used for this comparison is *Lena* of size 512 × 512, which is corrupted by both 20% fixed-valued and random-valued impulse noises, as in [6]. Table I lists the restoration results of different algorithms. From Table I, it is clear that for both fixed-valued and random-valued impulse noises, our method provides significant improvement over all the other approaches. In Fig. 2, we compare the restoration results of our method with those of SD-ROM for image *Lena* corrupted by random-valued impulse noise with various noise ratios ranging from 10%–30%. From Fig. 2, it is easy to see that our algorithm performs significantly better than the SD-ROM.

Next, we compare our method with two recently proposed techniques: the iterative procedure in [20] and the detail-preserving variational method (DPVM) in [21]. The test images used in [20] include three standard 256 × 256 gray-scale images: *Lena*, *Bridge*, and *Goldhill*, which are corrupted by 30% random-valued impulse noise. The restoration results of different algorithms are listed in Table II, which also includes that of ACWMF in [15]. Table II shows clearly that our algorithm outperforms all other three techniques for all the test images.

Finally, the performance of our proposed algorithm is compared with that of the homogeneity level information-based

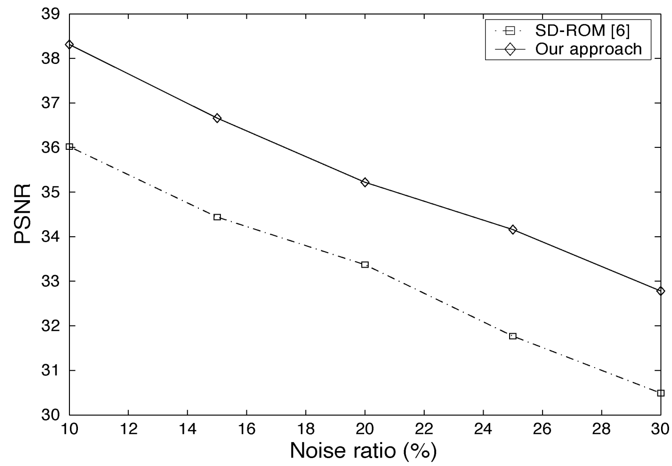


Fig. 2. Comparison of restoration results in PSNR for image *Lena* of size 512 × 512 corrupted with various ratios of random-valued impulse noise.

TABLE II
COMPARATIVE RESULTS IN PSNR (dB) FOR STANDARD IMAGES *Lena*, *Bridge*, AND *Goldhill* OF SIZE 256 × 256 CORRUPTED BY 30% RANDOM-VALUED IMPULSE NOISE

Algorithm	*Lena*	*Bridge*	*Goldhill*
ACWMF [15]	27.18	22.21	26.57
DPVM [21]	27.29	22.44	27.13
Iterative procedure [20]	28.33	22.76	27.52
Our approach	**28.48**	**24.62**	**28.61**

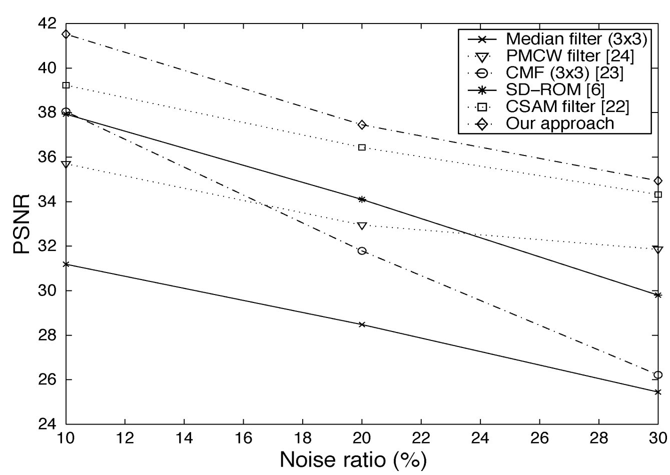


Fig. 3. Comparison of restoration results in PSNR for image *Lena* of size 512 × 512 corrupted with various ratios of fixed-valued impulse noise.

(a) (b) (c)

Fig. 4. Restoration result for *Lena* by our proposed method. (a) Original image of *Lena*. (b) *Lena* corrupted by 20% fixed-valued impulse noise. (c) Restored image of *Lena*.

CSAM filter presented in a paper by Pok *et al.* [22]. In [22], image *Lena* of size 512×512 is corrupted by 10%, 20%, and 30% of fixed-valued impulse noise. Pok *et al.* also reported the best restoration results in PSNR of several other existing techniques [22]. We plot some of those data in Fig. 3 along with the results of our algorithm. From Fig. 3, it is obvious that our approach achieved significant improvement over other techniques. As a final remark, it should be mentioned that for all the experiments in this section, the parameters for our approach are fixed to show its robustness. Better performance could be achieved with more appropriately tuned parameters.

In Fig. 4, a restored image of *Lena* is presented, which shows that the proposed algorithm yields superior subjective quality with respect to impulse noise suppression and image detail preservation.

IV. Conclusion

In this letter, a novel detail-preserving algorithm is proposed for removing impulse noise efficiently from images. To demonstrate the superior performance of the proposed method, extensive experiments have been conducted on a variety of standard test images to compare our method with many other well-known techniques. Experimental results indicate that the proposed method performs significantly better than many other existing techniques.

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References

[1] J. Astola and P. Kuosmanen, *Fundamentals of Nonlinear Digital Filtering*. Roca Raton, FL: CRC, 1997.

[2] T. Sun and Y. Neuvo, "Detail-preserving median based filters in image processing," *Pattern Recognit. Lett.*, vol. 15, pp. 341–347, Apr. 1994.

[3] S. J. Ko and Y. H. Lee, "Center weighted median filters and their applications to image enhancement," *IEEE Trans. Circuits Syst.*, vol. 38, no. 9, pp. 984–993, Sep. 1991.

[4] R. C. Hardie and K. E. Barner, "Rank conditioned rank selection filters for signal restoration," *IEEE Trans. Image Process.*, vol. 3, no. 2, pp. 192–206, Mar. 1994.

[5] H. Lin and A. N. Willson, "Median filter with adaptive length," *IEEE Trans. Circuits Syst.*, vol. 35, no. 6, pp. 675–690, Jun. 1988.

[6] E. Abreu, M. Lightstone, S. K. Mitra, and K. Arakawa, "A new 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.

[7] H. Hwang and R. A. Haddad, "Adaptive median filters: New algorithms and results," *IEEE Trans. Signal Process.*, vol. 4, no. 4, pp. 499–502, Apr. 1995.

[8] K. Arakawa, "Median filters based on fuzzy rules and its application to image restoration," *Fuzzy Sets Syst.*, vol. 77, pp. 3–13, 1996.

[9] D. Zhang and Z. Wang, "Impulse noise detection and removal using fuzzy techniques," *Electron. Lett.*, vol. 33, no. 5, pp. 378–379, 1997.

[10] T. Chen, K. Ma, and L. Chen, "Tri-state median filter for image denoising," *IEEE Trans. Image Process.*, vol. 8, no. 12, pp. 1834–1838, Dec. 1999.

[11] D. Florencio and R. W. Schafer, "Decision-based median filter using local signal statistics," in *Proc. SPIE Symp. Visual Communications Image Processing*, Sep. 1994, vol. 2038, pp. 268–275.

[12] F. Russo and G. Ramponi, "A fuzzy filter for images corrupted by impulse noise," *IEEE Signal Process. Lett.*, vol. 3, no. 6, pp. 168–170, Jun. 1996.

[13] Z. Wang and D. Zhang, "Restoration of impulse noise corrupted images using long-range correlation," *IEEE Signal Process. Lett.*, vol. 5, no. 1, pp. 4–7, Jan. 1998.

[14] T. Chen and H. R. Wu, "Application of partition-based median type filters for suppressing noise in images," *IEEE Trans. Image Process.*, vol. 10, no. 6, pp. 829–836, Jun. 2001.

[15] ——, "Adaptive impulse detection using center-weighted median filters," *IEEE Signal Process. Lett.*, vol. 8, no. 1, pp. 1–3, Jan. 2001.

[16] 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.

[17] J. B. Bednar and T. L. Watt, "Alpha-trimmed means and their relationship to median filters," *IEEE Trans. Acoust., Speech, Signal Process.*, vol. ASSP-32, no. 1, pp. 145–153, Feb. 1984.

[18] A. C. Bovik, T. S. Huang, and D. C. Munson, "A generalization of median filtering using linear combinations of order statistics," *IEEE Trans. Acoust., Speech, Signal Process.*, vol. ASSP-31, no. 6, pp. 1342–1350, Dec. 1983.

[19] [Online]. Available: http://sipi.usc.edu/services/database/Database.html.

[20] R. H. Chan, C. Hu, and M. Nikolova, "An iterative procedure for removing random-valued impulse noise," *IEEE Signal Process. Lett.*, vol. 11, no. 12, pp. 921–924, Dec. 2004.

[21] M. Nikolova, "A variational approach to remove outliers and impulse noise," *J. Math. Imaging Vis.*, vol. 20, no. 1, pp. 99–120, 2004.

[22] G. Pok, J. C. Liu, and A. S. Nair, "Selective removal of impulse noise based on homogeneity level information," *IEEE Trans. Image Process.*, vol. 12, no. 1, pp. 85–92, Jan. 2003.

[23] T. Kasparis, N. S. Tzannes, and Q. Chen, "Detail-preserving adaptive conditional median filters," *J. Electron. Imaging*, vol. 1, no. 14, pp. 358–364, 1992.

[24] J. Wang, "Prescanned minmax center-weighted filters for image restoration," *Proc. Inst. Elect. Eng.*, vol. 146, no. 2, pp. 101–107, Apr. 1999.