A New Impulse Detector for Switching Median Filters

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***Abstract*—A new impulse noise detection technique for switching median filters is presented, which is based on the minimum absolute value of four convolutions obtained using one-dimensional Laplacian operators. Extensive simulations show that the proposed filter provides better performance than many of the existing switching median filters with comparable computational complexity. In particular, the proposed filter is directed toward improved line preservation.**

***Index Terms*—Impulse detection, median filter.**

I. Introduction

A large number of algorithms have been proposed to remove impulse noise while preserving image details. Among them, the median filter and its modifications [1] are used widely because of their effective noise suppression capability. However, most of the median filters are implemented uniformly across the image and thus tend to modify both noise and noise-free pixels. Consequently, the effective removal of impulse is often accomplished at the expense of blurred and distorted features. Recently, the use of a switching scheme in impulse removal has attracted more attention because it can avoid the damage of good pixels by employing an impulse detector to determine which pixels should be filtered [3]–[7]. The switching median (SM) filters [3]–[5] have been shown to be simple and yet more effective than uniformly applied methods, in which a median and/or a weighted median (WM) filter is usually used to detect impulses. However, the median-based detector fails to distinguish thin lines from impulses. Accordingly, the thin lines are interpreted as impulses and removed. A rank-ordered mean (ROM)-based and a soft-switching impulse detector were shown to work well under high noise corruption but at the cost of significantly increasing computational complexity [6], [7]. In this letter, we propose a simple impulse detector for the SM filters that exhibits better impulse detection ability than other detectors. In particular, it can successfully preserve thin lines and other detail features. Both the simulation results and computational complexity analysis show that the proposed method is better than many of the existing switching schemes.

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II. Impulse Detection

The impulse detection is usually based on the following two assumptions: 1) a noise-free image consists of locally smoothly varying areas separated by edges and 2) a noise pixel takes a gray value substantially larger or smaller than those of its neighbors. Let x_{ij} and y_{ij} represent the pixel values at position (i, j) in the corrupted and restored images, respectively. The standard median filter outputs the median value of the samples in the $(2N+1) \times (2N+1)$ window centered at x_{ij}, i.e.,

$$m_{ij} = \text{median}\left\{x_{i-N,j-N}, \ldots, x_{ij}, \ldots, x_{i+N,j+N}\right\}. \quad (1)$$

To judge whether x_{ij} is an impulse, the median-based impulse detector [3] measures $|x_{ij} - m_{ij}|$ and compares it with a predefined threshold T_1

$$\alpha_{ij} = \begin{cases} 1, & |x_{ij} - mij| > T_1 \\ 0, & |x_{ij} - m_{ij}| \le T_1. \end{cases} \quad (2)$$

$\alpha_{ij} = 1$ means x_{ij} is a corrupted pixel; otherwise x_{ij} is noise-free. The output of the SM filter is obtained by

$$y_{ij} = \alpha_{ij} \cdot m_{ij} + (1 - \alpha_{ij}) \cdot x_{ij}. \quad (3)$$

It is well known that the median filter cannot distinguish thin lines from impulses. Accordingly, the median-based impulse detector will interpret thin lines as impulses and lead to the removal of thin lines from images. We propose a simple impulse detector to overcome this problem next.

The input image is first convolved with a set of convolution kernels. Here, four one-dimensional Laplacian operators as shown in Fig. 1 are used, each of which is sensitive to edges in a different orientation. Then, the minimum absolute value of these four convolutions (denoted as r_{ij}) is used for impulse detection, which can be represented as

$$r_{ij} = \min\left\{|x_{ij} \otimes K_p| : \ p = 1 \text{ to } 4\right\} \quad (4)$$

where K_p is the pth kernel, and $\otimes$ denotes a convolution operation.

The value of r_{ij} detects impulses due to the following reasons.

1) r_{ij} is large when the current pixel is an isolated impulse because the four convolutions are large and almost the same.
2) r_{ij} is small when the current pixel is a noise-free flat-region pixel because the four convolutions are close to zero.
3) r_{ij} is small also when the current pixel is an edge (including thin line) pixel because one of the convolutions is

0	0	0	0	0
0	0	0	0	0
-1	-1	4	-1	-1
0	0	0	0	0
0	0	0	0	0

0	0	-1	0	0
0	0	-1	0	0
0	0	4	0	0
0	0	-1	0	0
0	0	-1	0	0

-1	0	0	0	0
0	-1	0	0	0
0	0	4	0	0
0	0	0	-1	0
0	0	0	0	-1

0	0	0	0	-1
0	0	0	-1	0
0	0	4	0	0
0	-1	0	0	0
-1	0	0	0	0

Fig. 1. Four 5×5 convolution kernels.

very small (close to zero) although the other three might be large.

From the above analysis, r_{ij} is large when x_{ij} is corrupted by noise, and r_{ij} is small when x_{ij} is noise-free whether or not it is a flat-region, edge, or thin-line pixel. So, we can compare r_{ij} with a threshold T to determine whether a pixel is corrupted, i.e.,

$$\alpha_{ij} = \begin{cases} 1, & r_{ij} > T \\ 0, & r_{ij} \leq T. \end{cases} \tag{5}$$

Obviously, the threshold T affects the performance of impulse detection. It is not easy to derive an optimal threshold through analytical formulation. But we can determine a reasonable threshold using computer simulations.

III. Simulation Results

Computer simulations are carried out to assess the performance of the proposed impulse detector using a variety of test images. Mean square error (MSE) is used to give a quantitative evaluation on the filtering results.

We first study the effects of T on the performance of impulse detection. Fig. 2 shows the MSE values obtained by varying the threshold using the test image "Bridge" that is corrupted by 20% noise. It is seen that the MSE performance can be improved using our proposed method, and the effect of T on MSE is not so significant for our method in comparison with other detectors. Similar results are obtained after we test other images and noise levels.

Next, the performance of the proposed filer is compared with other switching (median-based [3], WM-based [3], tristate [5], and ROM-based [6]) and nonswitching (median, 2LM+ [2]) filters. The 2LM+ filter is selected because of its proven capability of preserving thin lines. The thresholds for the median-based, WM-based, and tristate impulse detectors are 40, 40, and 20 (used in [3] and [5]), and that for our detector is 116. The window size for the median filter is 3×3, and the weights for the WM-based detector is [1,3,1; 3,5,3; 1,3,1]. The window sizes for the first and second levels of the 2LM+ filter are 5×5 and 3×3, respectively. In order to test the effects of window size on MSE, we also simulated our method using 7×7 and 9×9 window sizes. We have tested ten images and only the MSE of the image "Bridge" and "Boat," and the average MSE of ten images are shown in Fig. 3 due to the letter length limitation. The noise ratio ranges from 5%–40%. It is seen that the performance of our algorithm (the lowest three curves) is better than the other filters when the noise ratio is larger than about 6.25%. On the other hand, the WM-based SM filter gives the lowest error when the noise percentage is smaller than 6.25%. This is because there are almost no noise blotches present in such a low noise percentage. It can be also seen that a smaller MSE can be obtained if the window size is increased in our method. Finally, we can see that SM filters normally have better performance than nonswitching filters. It is worth noting that the same conclusions can be obtained from every image we tested, although their results are not shown due to the page limitation.

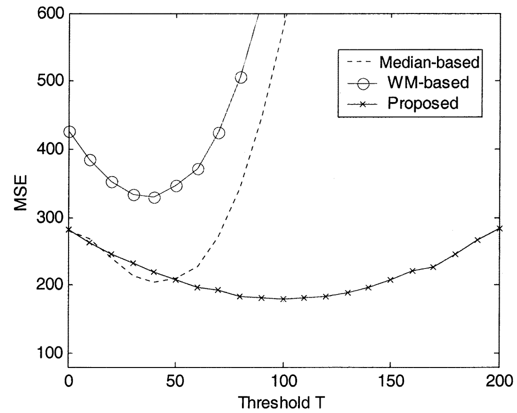


Fig. 2. MSE versus the threshold T for different SM filters.

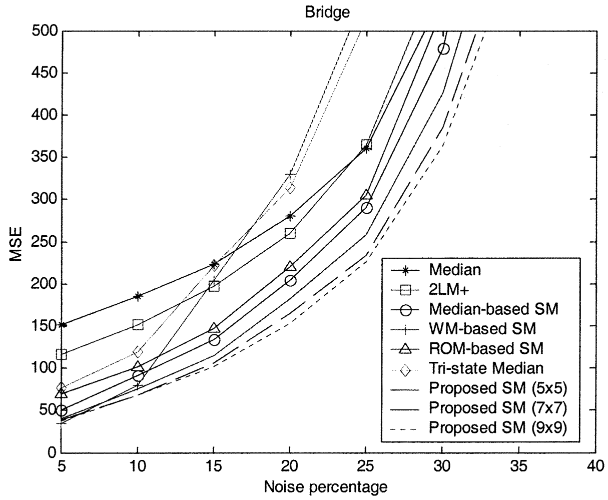
Fig. 4 shows the subjective visual qualities of the filtered images using various filters for the image "Bridge" as an exmaple. Fig. 4(a) and (b) shows the noise-free image and noisy image corrupted with 10% impulse noise, respectively. It can be seen from Fig. 4(c) that the simple median filter suppresses the impulses but introduces a blur effect. The median-based and ROM-based switching filters provide better results, but they remove some image details, especially thin lines. On the other hand, the WM-based and tristate median filters can preserve image details, but many impulses remain in the image, as seen from Fig. 4(f) and (g). Fig. 4(h) is the result of using a 2LM+ filter, in which some thin lines are persevered, but in which a blur effect is introduced. Fig. 4(i) shows the restored images using our proposed method with a 5×5 window size. It is seen that the proposed filter can remove most of the noise pixels while preserving image detail very well.

IV. Computational Complexity

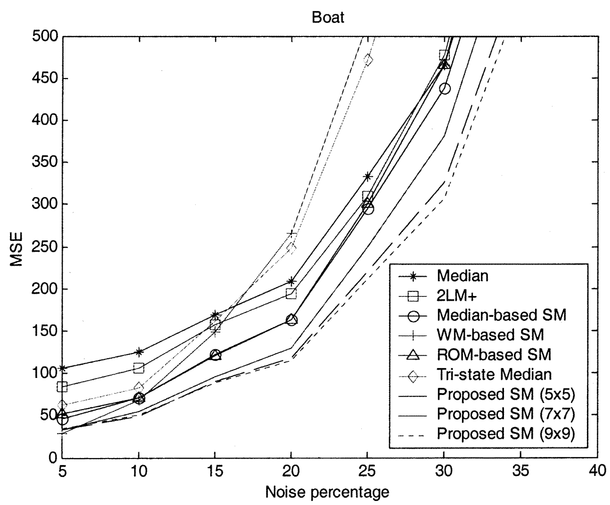
We perform a short analysis of the computational efficiency of the filters mentioned in Section III. In the following analysis, the window size of the median filter is assumed to be $N \times N$.

The simple median filter requires $2N^2 \mathrm{Log} N$ compare/swap operations in an optimal situation using a Quicksort algorithm. In the worst case, the number of operations is proportional to N^4.

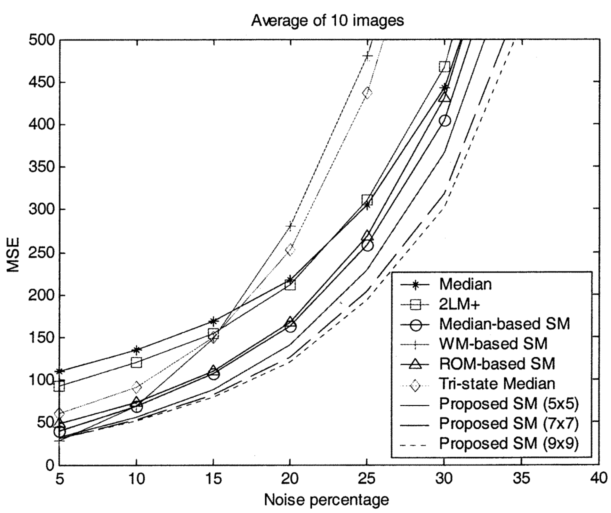
The 2LM+ filter [2] uses two levels of median filters. The first level has two templates in which each has $2N-1$ pixels to sort.



(a)



(b)



(c)

Fig. 3. MSE values for different filters operating on the image (a) "Bridge," (b) "Boat, " and (c) ten images (average).

The second level needs to find the median of three pixels. Thus, the total number of compare/swap operations in an optimal situation is $2(2N-1)\mathrm{Log}(2N-1)+3$.

The median-based SM filter [3] uses two median filtering operations (one for impulse detection and the other for noise removal) and one threshold comparison. So, it requires at least $4N^2\mathrm{Log}N+1$ compare/swap operations. However, if we consider the fact that the median filtering operation is applied only to noisy pixels, the number of operations can be significantly reduced as $(1+p)2N^2\mathrm{Log}N+1$, where p is the noise ratio and is normally smaller than 0.4.

The complexity of WM-based, ROM-based, and tristate SM filters is not analyzed here because they require many more sorting operations than the median-based SM filters.

The proposed impulse detector uses four convolutions, one minimum of four values, and a threshold comparison. By using our templates, the four convolutions can be simplified to four multiplications and $4(M-1)$ subtractions, where $M \times M$ is the detector window size. Since the four multiplications are identical (four times the central pixel value), the number of multiplications required can be reduced to be one, and this multiplication is equivalent to three additions (or two shifts). Thus, the total number of operations in the proposed SM filter with noise ratio of p is

$$4(M-1)+3 \text{ additions or subtractions}$$

and

$$p \times 2N^2\mathrm{Log}N + 4 \text{ compare/swap.}$$

The above analysis gives the number of operations required for one image pixel, and it is straightforward to obtain the total computational cost simply by multiplying by the image size. For better comparison, the window sizes specified in Section III and 40% noise are substituted to the above analysis, and we can obtain the following number of operations:

Simple Median	18 $\mathrm{Log}3$ compare/swap;
2LM+	36 $\mathrm{Log}3+3$ compare/swap;
Median-based SM	25.2 $\mathrm{Log}3+1$ compare/swap;
Proposed SM	7.2 $\mathrm{Log}3+4$ compare/swap, 19 additions or subtractions.

It is seen that the number of compare/swap operations in the proposed filter is much smaller than other filters. Although some additions or subtractions are required, they are faster than compare/swap operations. This is because an addition or a subtraction is just an operation, while a comparison must be implemented by at least two operations in assembly language: a subtraction followed by a conditional jump operation, and if swap is needed, three additional assignment operations are required. Accordingly, the proposed filter has the lowest computational complexity.

V. Conclusion

We have proposed an improved impulse detector that can effectively separate noise and noise-free pixels. In particular, it prevents the removal of fine details such as thin lines from the images and thus provides improved impulse detection ability. Both the simulation and computational complexity analysis show that the proposed method is better than many of the existing SM filters such as the median-based, WM-based, ROM-based, and tristate SM filters. The MSE curves in Fig. 3 show that MSE increases significantly when the noise becomes

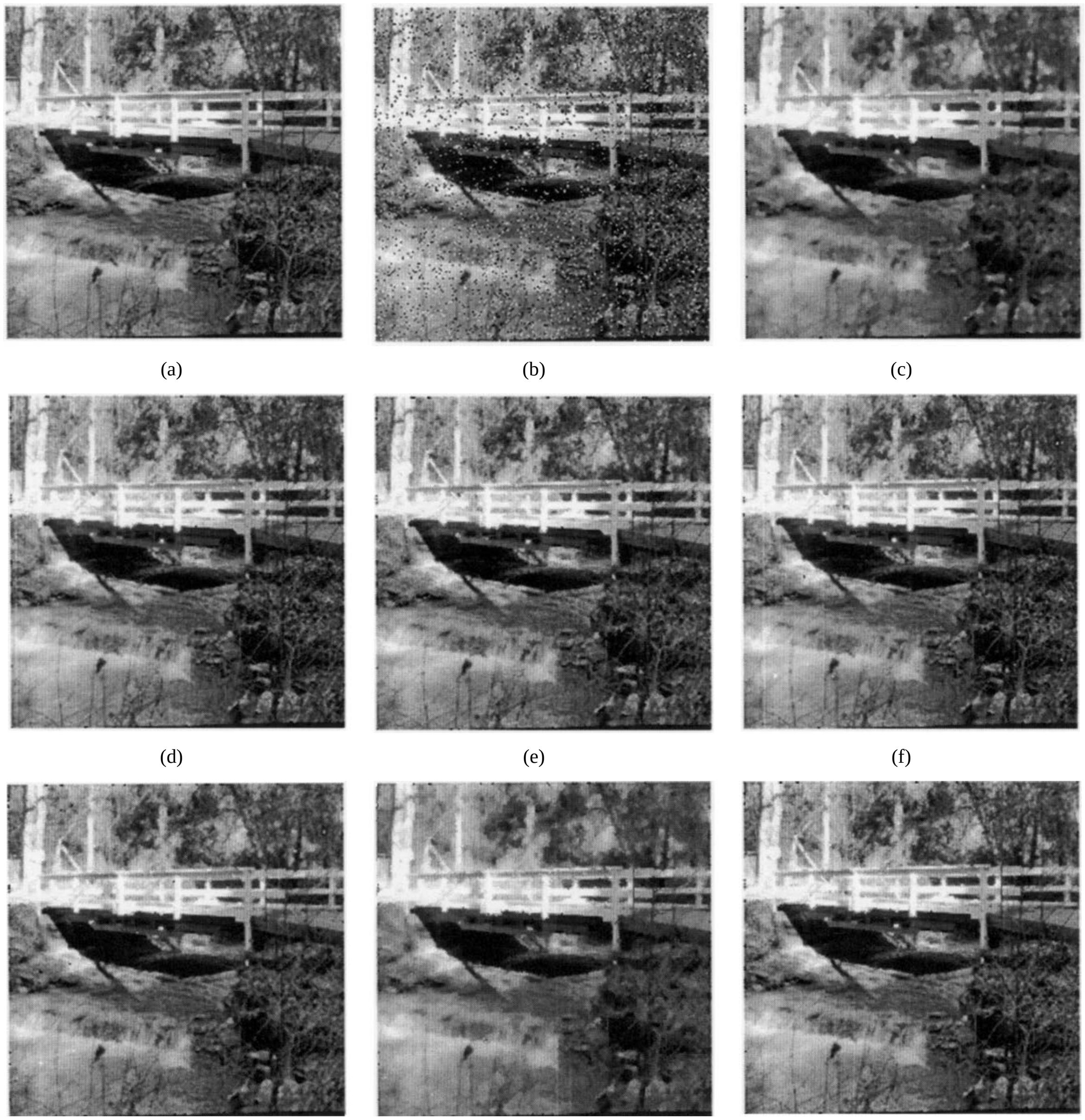


Fig. 4. Restoration results of different filters. (a) Noise-free image "Bridge." (b) Corrupted image with 10% noise. (c) Median filter. (d) Median-based SM filter. (e) ROM-based switching filter. (f) WM-based SM filter. (g) Tristate median filter. (h) 2LM+ filter. (i) Proposed SM filter with a 5×5 window.

heavy (after approximately 30%) for every filtering algorithm considered here.

It is supposed to be useful if we add more kernels to detect lines in directions other than horizontal, vertical, and two diagonals. However, the ranges of the convolutions obtained using the kernels for these directions may be different from that obtained using the four proposed kernels, since they may have different number of pixels. Accordingly, normalization may be needed. In the future, various adaptive and iterative techniques can be considered to incorporate in our scheme to further improve the performance.

References

[1] J. Astola and P. Kuosmanen, *Fundamentals of Nonlinear Digital Filtering*. New York: CRC, 1997.

[2] I. Pitas and A. N. Venetsanooulos, *Nonlinear Digital Filters: Principles and Applications*. Boston, MA: Kluwer, 1990.

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

[4] Z. Wang and D. Zhang, "Progressive switching median filter for the removal of impulse noise from highly corrupted images," *IEEE Trans. Circuits Syst. II*, vol. 46, pp. 78–80, Jan. 1999.

[5] T. Chen, K.-K. Ma, and L.-H. Chen, "Tri-state median filter for image denoising," *IEEE Trans. Image Processing*, vol. 8, pp. 1834–1838, Dec. 1999.

[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 Processing*, vol. 5, pp. 1012–1025, 1996.

[7] H.-L. Eng and K.-K. Ma, "Noise adaptive soft-switching median filter," *IEEE Trans. Image Processing*, vol. 10, pp. 242–251, Feb. 2001.