Short Paper

Salt-Pepper Impulse Noise Detection and Removal Using Multiple Thresholds for Image Restoration*

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In this paper, a novel decision-based filter, called the multiple thresholds switching (MTS) filter, is proposed to restore images corrupted by salt-pepper impulse noise. The filter is based on a detection-estimation strategy. The impulse detection algorithm is used before the filtering process, and therefore only the noise-corrupted pixels are replaced with the estimated central noise-free ordered mean value in the current filter window. The new impulse detector, which uses multiple thresholds with multiple neighborhood information of the signal in the filter window, is very precise, while avoiding an undue increase in computational complexity. For impulse noise suppression without smearing fine details and edges in the image, extensive experimental results demonstrate that our scheme performs significantly better than many existing, well-accepted decision-based methods.

Keywords: image restoration, filter, threshold, impulse detector, impulse noise

1. INTRODUCTION

Images are often corrupted by impulse noise when they are recorded by noisy sensors or sent over noisy transmission channels. Many impulse noise removal techniques have been developed to suppress impulse noise while preserving image details [1-7]. The median filter, the most popular kind of nonlinear filter, has been extensively used for the removal of impulse noise due to its simplicity. However, the median filter tends to blur fine details and lines in many cases. To avoid damage to good pixels, decision-based median filters realized by thresholding operations have been introduced in some recently

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published works [8-16]. In general, the decision-based filtering procedure consists of the following two steps: an impulse detector that classifies the input pixels as either noise-corrupted or noise-free, and a noise reduction filter that modifies only those pixels that are classified as noise-corrupted. In general, the main issue concerning the design of the decision-based median filter focuses on how to extract features from the local information and establish the decision rule, in such a way to distinguish noise-free pixels from contaminated ones as precisely as possible. In addition, to achieve high noise reduction with fine detail preservation, it is also crucial to apply the optimal threshold value to the local signal statistics. Usually a trade-off exists between noise reduction and detail preservation.

In this paper, we propose a novel decision-based filter, named the multiple thresholds switching (MTS) filter, to overcome the drawbacks of the above methods. Basically, the proposed filter takes a new impulse detection strategy to build the decision rule and practice the threshold function. The new impulse detection approach based on multiple thresholds considers multiple neighborhood information of the filter window to judge whether impulse noise exists. The new impulse detector is very precise without, while avoiding an increase in computational complexity. The impulse detection algorithm is used before the filtering process starts, and therefore only the noise-corrupted pixels are replaced with the estimated central noise-free ordered mean value in the current filter window. Extensive experimental results demonstrate that the new filter is capable of preserving more details while effectively suppressing impulse noise in corrupted images.

The rest of this paper is organized as follows. In section 2, some basic concepts are reviewed, and the noise model defined. Then, in section 3, the design of the new MTS filter is presented in detail. In section 4, some experimental results demonstrate that the proposed MTS filter can actually outperform other decision-based filters. Finally, the conclusion is given in section 5.

2. BASIC CONCEPT AND IMPULSE NOISE MODEL

Before introducing the proposed MTS filter, some notation must be defined first. Let the filter window $w(k)$ (or a sliding window) sized $2n + 1$ cover the image X from left to right, top to bottom in a raster scan fashion.

$$w(k) = (x_{-n}(k), \ldots, x_{-1}(k), x_0(k), x_1(k), \ldots, x_n(k)), \tag{1}$$

where $x_0(k)$ (or $x(k)$) is the original central vector-valued pixel at location k. In this work, we consider a 3×3 filter window $w(k)$ centered around $x_0(k)$

$$w(k) = (x_{-4}(k), \ldots, x_{-1}(k), x_0(k), x_1(k), \ldots, x_4(k)). \tag{2}$$

Impulse noise can appear because of a random bit error on a communication channel. In this work, the source images are corrupted only by salt-pepper impulse noise, which means a noisy pixel has a high value due to positive impulse noise, or has a low value due to a negative impulse noise.

3. DESIGN OF THE MTS FILTER

3.1 A New Approach to Judge Whether an Impulse Noise Exists

Basically, the proposed MTS filter uses multiple thresholds to classify the signal as either noise-free or noise-corrupted so that only noisy signals are filtered while good signals are preserved. Fig. 1 shows the structure of the new MTS filter. In the detection process, if $x(k)$ is judged to be the maximum or minimum in the filter window, then the decision rules (threshold functions) are used on the neighboring pixels of $x(k)$ to decide whether it is a noise corrupted pixel. To identify corrupted pixels, input pixels can be separated into two classes, A and B. Pixels in class A are supposedly much more likely to be impulses than those in class B. To make sure that this happens, first, we check $x(k)$ to see whether it is a maximum or minimum in the filter window. If $x(k)$ is a maximum or minimum, it will be classified into class A, otherwise it will be classified into class B. When $x(k)$ is classified into class A, the pixels of the 3 × 3 filter window (excluding $x(k)$) are sorted in ascending order. The sorted vector can be defined as

$$s(k) = (s_1(k), s_2(k), \dots, s_8(k)), \tag{3}$$

where $s_1(k)$, $s_2(k)$, …, $s_8(k)$ are the elements of $w(k)$ arranged in ascending order. The differences between the input pixel $x(k)$ and each of the elements of $s(k)$ provide an efficient measurement to identify noisy pixels.

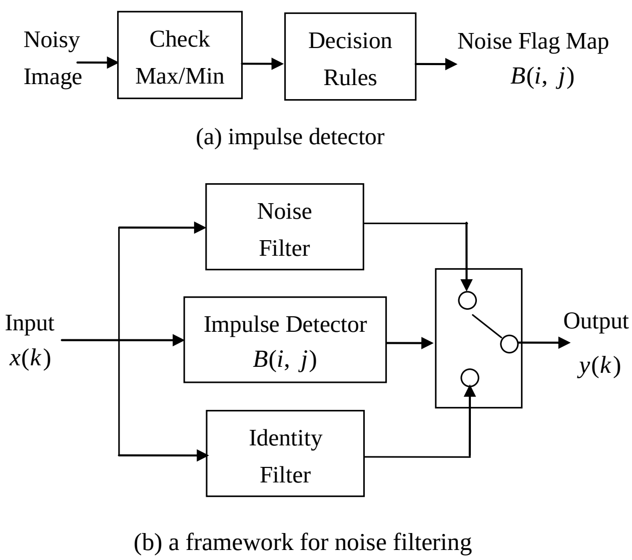


Fig. 1. Structure of the MTS filter.

Definition 1 $d(k) = (d_1(k), d_2(k), \dots, d_8(k))$ where

$$d_i(k) = \begin{cases} x(k) - s_{9-i}(k) & \text{if } x(k) \geq s_i(k),\ i = 1, 2, ..., 8 \\ s_i(k) - x(k) & \text{otherwise} \end{cases}. \tag{4}$$

The grade-ordered difference $d_i(k) \in [0, 255]$ provides information about the likelihood of corruption for $x(k)$. Furthermore, the full differences from $d_1(k)$ through $d_8(k)$ in the current 3 × 3 filter window can reveal more information about pixels on a line or at an edge, even when highly corrupted impulses are present in the current filter window. Since $s_i(k)$ has been arranged in ascending order, Eq. (4) shows that $d_i(k) \in [0, 255]$ is also in ascending order. Thus, if any $d_1(k)$, $d_2(k)$, …, $d_8(k)$ is greater than the corresponding threshold value, then $x(k)$ is detected as corrupted by the impulse noise detector. The input pixel is detected as a noisy pixel if any of the following decision rules is true:

$$d_i(k) > T_i,\ i = 1, 2, \ldots, 8, \tag{5}$$

where T_1, T_2, …, T_8 are threshold values, $T_1 < T_2 < \ldots < T_8$. Then, the noise flag map $B(i, j)$ can record the location of the impulse noise in the noisy image.

$$B(i, j) = \begin{cases} 1, & \text{if } x(k) \text{ is classified to be noisy} \\ 0, & \text{otherwise} \end{cases}. \tag{6}$$

Based on the heuristic approach, proper threshold values can be easily obtained through extensive empirical tests involving a large variety of test images. The first threshold T_1 is found experimentally by applying the MTS filter, and then the other thresholds can be expanded and obtained one by one. For example, when the one threshold value T_1 is tested, $x(k)$ can be indicated to be either corrupted or not according to the value of T_1. After that, along with threshold value T_1, the second threshold value T_2 ($T_2 > T_1$) can be tested. Likewise, each of the other threshold values T_3, T_4, …, T_8 can be obtained based on the former threshold values. After testing a large variety of images, we can pick out the most suitable threshold values to obtain the best results and highest PSNR values. Note that the more grade-ordered differences d_i considered, the more information about noise can be obtained. That is, the more decision thresholds have are considered, the more accurately the impulse noise can be detected. The effect of the number of thresholds and threshold values T_i on the scheme is discussed in the next section.

3.2 Noise Filtering

If the input pixel is classified as an impulse according to the binary noise flag map $B(i, j)$, the pixel value is replaced by the estimated central noise-free ordered mean value. Otherwise, its original intensity is the output. However, the estimated mean value here is computed from only the noise-free pixels within the filter window $w(k)$. The noise-free pixels can be sorted in ascending order, which defines the vector as

$$f(k) = (f_1(k), f_2(k), \ldots, f_C(k)), \tag{7}$$

where $f_1(k) \leq f_2(k) \leq \ldots \leq f_C(k)$ are elements of $w(k)$ and are good pixels according to their corresponding binary noise flag map $B(i, j)$. C denotes the number of all the pixels with $B(i, j) = 0$ in the filter window $w(k)$,

$$CMEAN\ f(k) = \begin{cases} y'(k) & \text{if } C = 0 \\ (f_{C/2}(k) + f_{C/2+1}(k))/2 & \text{if } C > 0 \end{cases}, \tag{8}$$

where $CMEAN$ refers to the central mean operation and $y'(k)$ is the filtering result of the left neighboring pixel of $x(k)$.

The new nonlinear MTS filter is defined as

$$y(k) = \alpha x(k) + (1 - \alpha) CMEAN\ f(k), \tag{9}$$

where the coefficient α is 0 or 1. The coefficient α is determined by the binary noise flag map $B(i, j)$ at $x(k)$. If $B(i, j)$ is 1, the pixel $x(k)$ is noise, the coefficient α is set to 0, and the output $y(k)$ of the noise filtering process is $CMEAN\ f(k)$. Otherwise, if $B(i, j)$ is 0, the coefficient α is set to 1 and the output $y(k)$ is the identity $x(k)$. The result is that the new MTS filter can suppress impulse noise without degrading the quality of the fine details.

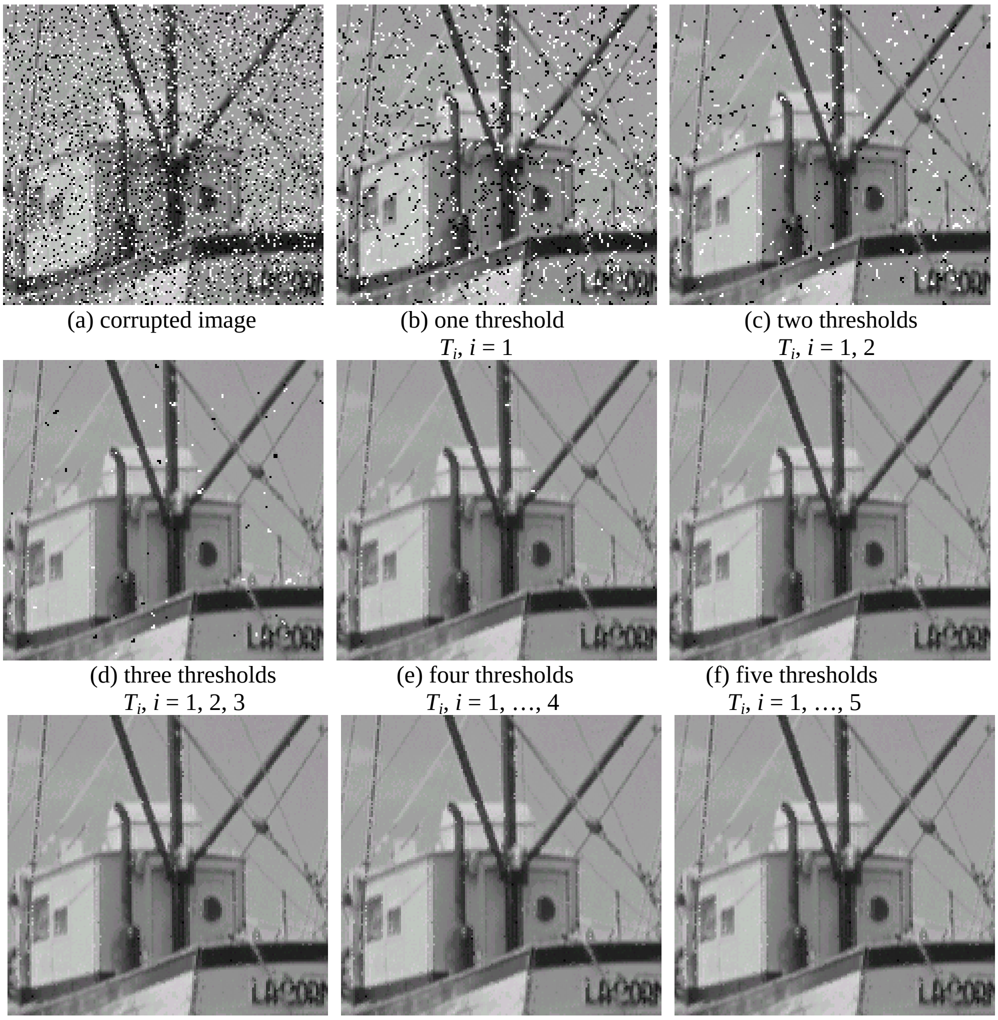
4. EXPERIMENTAL RESULTS

In our experiments, a set of 512 × 512 test images corrupted with salt- pepper impulse noise are used. The following experiments have been conducted to examine the effectiveness of our new filter.

The influence of the number of thresholds and the threshold values T_i in Eq. (5) are first investigated. Based on the heuristic approach, the threshold values are obtained experimentally for different test images. For the majority of images we tested, the most suitable threshold values employed by the MTS filter are approximately $T_1 = 20$, $T_2 = 25$, $T_3 = 30$, $T_4 = 50$, $T_6 = 60$, $T_7 = 220$ and $T_8 = 250$ so that we can obtain the best results and highest PSNR values. The restoration results for the corrupted 'Boat' image by 20% impulse versus various numbers of thresholds are shown in Fig. 2. Fig. 3 shows the PSNR comparison results of the restored images corrupted by 20% impulse versus various numbers of thresholds. In addition, Fig. 4 shows the PSNR comparison results of the restored 'Boat' image, where the impulse corruption ratio varies from 10% to 30% with various numbers of thresholds. According to the results from Figs. 3 and 4, when the number of thresholds reaches 5, satisfactory results can be obtained. However, the most suitable number of thresholds is 8; that is, the full grade-ordered difference d_i, $i = 1, 2, \ldots, 8$ in the 3 × 3 filter window taken into account will lead to the best-restored image.

The second experiment is to compare the MTS filter with the standard median (MED) filter, the CWM filter [7], the switching scheme I (SWM-I) filter [12], the detection-estimation (DET-EST) filter [10], the minmax (MINMAX) filter [16], the signal-dependent rank order mean (SD-ROM) filter [14], the tri-state median (TSM) filter [13], and the progressive switching median (PSM) filter [15] in terms of noise removal capability (measured in PSNR) and perceptual quality. The threshold values $T_1 = 8$, $T_2 =$

20, T_3 = 40 and T_4 = 50 are used in the SD-ROM filter in our experiments. In addition, the threshold value T = 41 is used in the PSM filter in our experiments. Table 1 shows the comparative restoration results in PSNR (dB) when the impulse noise rate is 20%. Apparently, as Table 1 reveals, the proposed filter gives the best restoration performance in terms of PSNR. Fig. 5 shows the restoration results and the MAE values for the 'Lenna' image corrupted by 20% impulse noise and filtered by MED, PSM, SD-ROM and MTS. Visually, the MTS filter produces a better subjective visual quality of restored image and has the smallest MAE.



(a) corrupted image; (b) one threshold T_i, i = 1; (c) two thresholds T_i, i = 1, 2;
(d) three thresholds T_i, i = 1, 2, 3; (e) four thresholds T_i, i = 1, …, 4; (f) five thresholds T_i, i = 1, …, 5;
(g) six thresholds T_i, i = 1, …, 6; (h) seven thresholds T_i, i = 1, …, 7; (i) eight thresholds T_i, i = 1, …, 8

Fig. 2. Restoration results of corrupted 'Boat' image by 20% impulse noise with various numbers of thresholds.

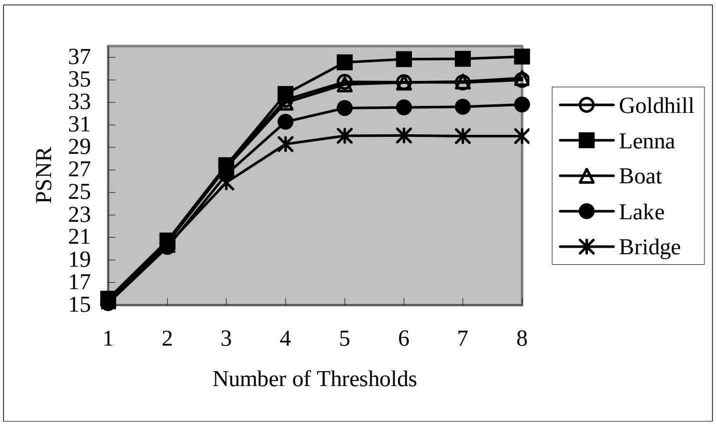


Fig. 3. The effect of various numbers of thresholds on different images corrupted by 20% impulse noise.

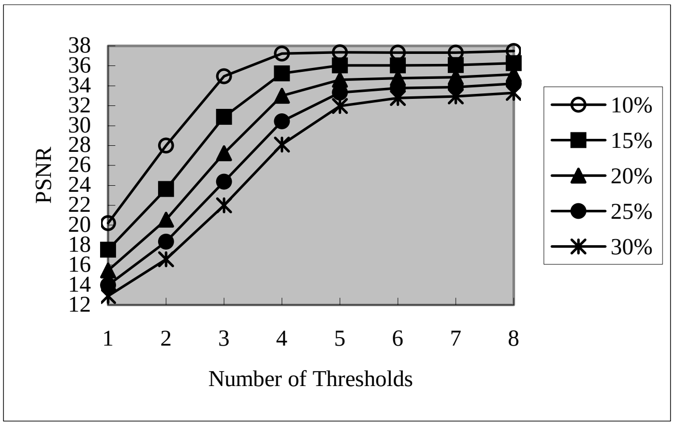


Fig. 4. The effect of various numbers of thresholds on the 'Boat' image with the corruption ratio ranging from 10% to 30%.

Table 1. Comparative restoration results in PSNR (dB) for 20% impulse noise.

FILTERS	IMAGES				
	Lenna	Goldhill	Boat	Bridge	Lake
MED	30.18	28.84	29.20	24.98	27.19
CWM	30.38	29.87	29.81	25.67	28.11
SWM-I	31.51	30.55	30.33	26.23	28.47
DET-EST	31.07	30.22	30.05	26.31	27.92
MINMAX	32.15	30.06	30.41	25.28	28.22
TSM	31.84	31.55	31.16	27.65	29.73
PSM	34.47	30.99	30.38	26.32	28.95
SD-ROM	31.72	31.16	30.96	27.23	28.94
MTS	37.06	34.99	35.15	30.07	32.59

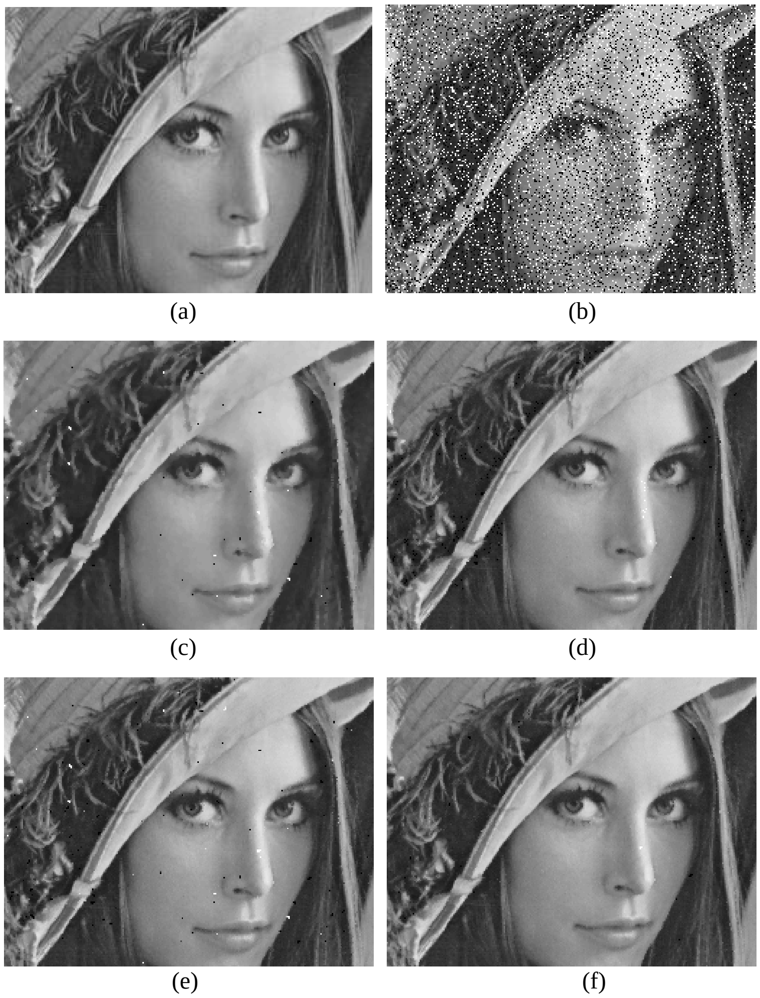


Fig. 5. Subjective visual qualities of restored 'Lenna' images: (a) original image (b) corrupted by 20% impulse noise, and filtered by (c) MED filter, MAE = 3.44, (d) PSM filter, MAE = 1.36, (e) SD-ROM filter, MAE = 1.37 and (f) MTS filter, MAE = 1.24.

5. CONCLUSIONS

In this paper, we have presented a new efficient decision-based filter, the multiple thresholds switching filter, for image restoration. Because the new impulse detection mechanism can accurately tell where noise is, only the noise-corrupted pixels are replaced with the estimated central noise-free ordered mean value. As a result, the restored images can preserve perceptual details and edges in the image while effectively suppressing impulse noise. The experimental results included in this paper have demonstrated that the proposed filter significantly outperforms a number of well-accepted decision-based filters.

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