A New Efficient Impulse Noise Detection based on Rank Estimation

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Abstract

In this paper, we present a new impulsive noise detection technique. To remove the impulse noise without detail loss, only corrupted pixels must be filtered. In order to identify the corrupted pixels, a new impulse detector based on rank and value estimations of the current pixel is proposed. Based on the rank and value estimations of the current pixel, the new proposed method provides excellent statistics for detecting an impulse noise while reducing the probability of detecting image details as impulses. The proposed detection is efficient and can be used with any noise removal filter. Simulation results show that the proposed method significantly outperforms many other well-known detection techniques in terms of image restoration and noise detection.

Keywords : Impulse noise detection, median filter, rank-order filter

I. Introduction

In image processing, the median filter has been extensively used for the removal of impulse noise due to its computational simplicity. Despite its effectiveness in removing noise, the median filter tends to remove details of the image. To suppress impulse noise from images without loss of image detail, a number of modified median and rank-type filters, such as weighted median filters [1,2], rank-order type filters [3-5], are presented. To avoid the damage of uncorrupted pixels, impulse-detection-based filters [6-13] are also introduced. Basically, the impulse-detection-based filters constitute two tasks: identification of corrupted pixels and filtering operation only on those corrupted pixels. Thus, the effectiveness of these schemes lies on the accuracy and robustness of detection of noisy pixels and efficiency of the filtering methodology employed.

In the detection-based filters, main drawback is that the noisy pixels are replaced by some median value in their vicinity, e.g., median [4],[6], rank-ordered mean [9-11], linearly weighted rank order [13], and minimum-maximum exclusive mean [8], without considering local details. Especially when the noise level is high, details and edges are not recovered satisfactorily.

In [14], it is shown that the directional interpolation filter with excluding minimum and maximum pixels effectively reduces the impulse noises with preserving detail features. Another main issue concerning the design of the detection-based filter focuses on how to extract local image statistics and establish the detection rule. To achieve high noise reduction with fine detail preservation, it is also crucial to apply the optimal threshold value to the local signal statistics. For a highly corrupted image, the sophisticated noise detections [15,16] are needed. The filters [15] and [16] demonstrate good filtering performance at the cost of increased computational complexity.

In this paper, we present a new impulsive noise detection technique that significantly outperforms many other well-known impulse detectors [6-13]. Based on the rank and value estimations of the current pixel, the new proposed method provides excellent statistics for detecting an impulse noise. Simulation results under various noise conditions are given to present the effectiveness of the proposed method. The rest of the paper is organized as follows: the conventional and proposed methods are explained in Sect. 2. Experiments are given in Sect. 3, and finally, conclusions are presented in Sect. 4.

II. Impulse Detection

Before introducing the impulse detection, some notation will be described. Let $x(n,m)$ for $(n,m) \in A = \{1, \cdots, N\} \times \{1, \cdots, M\}$ be the gray level of a

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N-by-M image X at pixel location (n,m). And let $S_{(n,m)}^{W}$ be the sample pixels in the window of size W^2 centered at (n,m),

$$S_{(n,m)}^{W}=\left\{x(n+k,m+l):-\frac{W-1}{2}\leq k,l\leq\frac{W-1}{2}\right\}. \quad (1)$$

Using rank operator O, the sample pixels in $S_{(n,m)}^{W}$ are ordered by rank,

$$O\left\{S_{(n,m)}^{W}\right\}=\left\{x_{(n,m)}^{1},x_{(n,m)}^{2},\cdots,x_{(n,m)}^{W^2}\right\} \quad (2)$$

where $x_{(n,m)}^{1}\leq x_{(n,m)}^{2}\leq\cdots\leq x_{(n,m)}^{W^2}$. The median of $S_{(n,m)}^{W}$, i.e., $x_{(n,m)}^{(W^2-1)/2+1}$, is denoted as $x_{(n,m)}^{MED}$.

A. Review of Impulse Detection

Since the difference between the level of an impulse and the median value in a local window is usually large, simple impulse detection method is to compare the center pixel to the median

$$d(n,m)=\left|x(n,m)-x_{(n,m)}^{MED}\right|. \quad (3)$$

Using Eq. (3) and switching scheme, progressive switching median (PSM) filter [6] is proposed, where both the impulse noise detector and the noise filter are applied progressively. Since any impulse is usually located near the first or last of rank-ordered pixels, the more robust noise detectors using Eq. (3) and the rank of center pixel are recently introduced in [12] and [13]:

$$\left[\left[R(x(n,m))\leq T_l\right]\vee\left[R(x(n,m))\geq T_u\right]\right]\wedge\left[d(n,m)\geq T_d\right] \quad (4)$$

where $R(\cdot)$ is the function that returns the rank (the position: from 1 to W^2) of an element, $\wedge$ and $\vee$ are the signs of conjunction and disjunction, respectively. If the condition (4) holds for some pixel $x(n,m)$, then this $x(n,m)$ is classified as corrupted by impulse noise. Note that T_d is a threshold and $1\leq T_l<T_u\leq W^2$. In [12], the detector using Eq. (3) and (4) is called an enhanced rank impulse detector (ERID). The ERID is shown to provide good results for impulsive noise detection and elimination by the median filter with minimal image smoothing. Figure 1 shows an example from the 20% corrupted Lena image, which verifies that statistics of $R(x(n,m))$ and $d(n,m)$ is a good indicator of impulse noise.

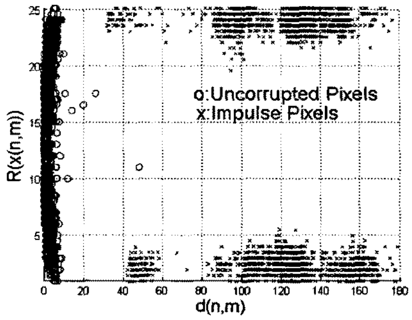


Fig. 1. Statistics of $R(x(n,m))$ and $d(n,m)$ obtained from the 20% corrupted Lena image with 5×5 window.

Instead of the median value $x_{(n,m)}^{MED}$ in Eq. (3), rank-ordered type filters are recently introduced for better noise detection and image restoration: rank-ordered mean (ROM) filter with multiple thresholds [9,10], linearly weighted rank order (LWRO) filter with iteration [13], and minimum-maximum exclusive mean (MMEM) filter [8]. The ROM, LWRO, and MMEM filters are given as follows:

$$x_{(n,m)}^{ROM}=\sum_{i=R_c}^{R_c+1}\frac{x^i(n,m)}{2} \quad (5)$$

$$x_{(n,m)}^{LWRO}=\sum_{i=1}^{W^2}\alpha_i x^i(n,m) \quad (6)$$

$$x_{(n,m)}^{MMEM}=\sum_{i=R_l}^{R_u}\beta x^i(n,m) \quad (7)$$

where R_c is a fixed central rank ($R_c\simeq MED$), $\sum_{i=1}^{W^2}\alpha_i=1$, and $\beta=1/\sum_{i=R_l}^{R_u}$. The R_l and R_u are ranks of the 2nd smallest and largest pixels such that $x_{(n,m)}^{R_l}>x_{(n,m)}^{1}$ and $x_{(n,m)}^{R_u}<x_{(n,m)}^{W^2}$, respectively. In general, $1<R_l<R_c<R_u<W^2$. For $\alpha_{MED}=1$ and $\alpha_i=0,\forall i(\neq MED)$, $x_{(n,m)}^{LWRO}\equiv x_{(n,m)}^{MED}$. Also note that $x_{(n,m)}^{MMEM}\equiv x_{(n,m)}^{ROM}$ for $R_l=R_c$ and $R_u=R_l+1$.

To remove both impulse and Gaussian noises, Garnett et al. [7] introduced local image statistics by rank-ordered absolute differences (ROAD) to identify the impulse noisy pixels, and incorporated it into a filter.

B. New Efficient Impulse Detection

As described in Sect. 2.A, detection-based approaches identify noisy pixels by comparing the output of the median filter ($x_{(n,m)}^{MED}$) or the average value of the filter windows ($x_{(n,m)}^{ROM},x_{(n,m)}^{LWRO},x_{(n,m)}^{MMEM}$) to the value of center pixel ($x(n,m)$). When the distance exceeds a threshold, the center pixel is regarded as a noise pixel. When an image has lots of detail components, however, a lot of mis-detections will occur and result in more degraded filtering performance. In addition, if a pixel is not corrupted, but still has the highest or lowest rank (e.g., if the pixel is part of an edge), it will be identified as an impulse.

To overcome these disadvantages, we apply new noise detection method using rank estimator. Rank estimator $\hat{R}(\cdot)$ for center pixel is defined as

$$\hat{R}(x(n,m))=\sum\sum_{k,l} w(k,l)R(x(n+k,m+l)) \quad (8)$$

where $w(k,l)$ is the normalized weighting function such that $w(k,l)=\frac{w^s(k,l)w^x(k,l)}{\sum\sum_{k,l} w^s(k,l)w^x(k,l)}$, $w^s(k,l)=e^{-(k^2+l^2)/2\sigma_W^2}$, and $w^x(k,l)=1$ if $x^1_{(n,m)}<x(n+k,m+l)<x^{W^2}_{(n,m)}$, otherwise 0. The degree of spatial spread σ_W is chosen based on the window size, i.e., $\sigma_W<W$. Note that $1<R_l\le\hat{R}(x(n,m))\le R_u<W^2$. Using the rank obtained from Eq. (8), the estimation of center pixel $\hat{x}(n,m)$ is given as the following rank-order interpolation:

$$\hat{x}(n,m)=\left(1-\widehat{R}^F\right)x^{\widehat{R}^I}_{(n,m)}+\widehat{R}^F x^{\widehat{R}^I+1}_{(n,m)} \quad (9)$$

where $\widehat{R}^I$ and $\widehat{R}^F$ are the integer and fractional part of $\hat{R}(\cdot)$, respectively. The value $\hat{x}(n,m)$ is interpolated by using rank-ordered pixels located around the center (n,m).

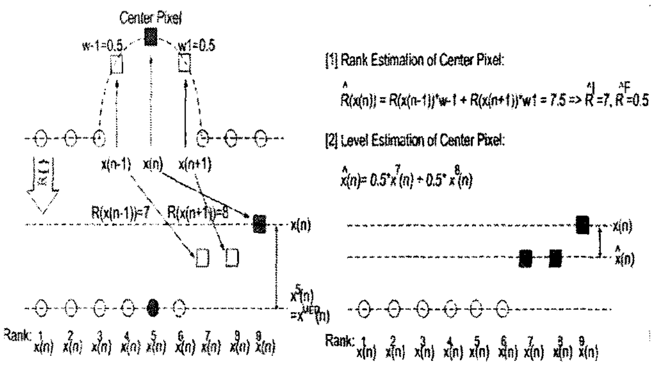


Fig. 2. Illustration of 1-D signal with bright detail: (a) $|x(n,m)-x^{MED}(n,m)|$, (b) $|x(n,m)-\hat{x}(n,m)|$.

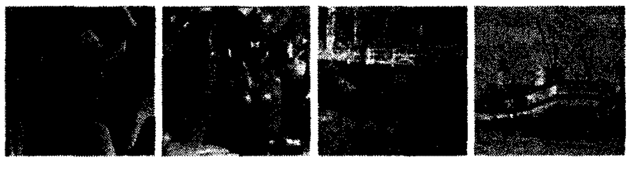
Figure 2 shows an illustrative example of 1-D bright detail signal. When $|x(n,m)-x^{MED}(n,m)|>T_d$ (see Fig. 2 (a)), the conventional method falsely identifies the detail signal as noise. For the corrupted center pixel, however, $|x(n,m)-x^{MED}(n,m)|\approx|x(n,m)-\hat{x}(n,m)|$. Therefore, the rank and value estimations of the center pixel, e.g., $\hat{R}(x(n,m))$ and $\hat{x}(n,m)$, provide excellent statistics for detecting an impulse noise and can be used for replacing the noisy pixel.

There are two models of impulse noise: salt-and-pepper and random-valued. In this paper, we focus on the detection of salt-and-pepper noise.

III. Simulation Results

In this section, we will compare the noise detection capability of the proposed method with other techniques. For performance evaluation, several popular images (512-by-512, 8-bit gray-level) shown in Fig. 3 are used.

Figure 4 displays quantitative results from the Lena image. The upper and lower dashed lines represent the mean $d(n,m)$ values for noise pixels and uncorrupted pixels, respectively. The vertical bars are standard deviation errors which demonstrate the significance of the difference. As shown in Fig. 4 (e), the mean $d(n,m)$ values of the noise pixels obtained from the proposed method are much higher than those of the uncorrupted pixels. The mean $d(n,m)$ values of the uncorrupted pixels also remain constant for very large amounts of noise, which implies that the choice of threshold value T_d is insensitive to the noise ratio. Compared with other methods, the standard deviation errors of the uncorrupted pixels obtained from the proposed method are very small, which also implies that the smoothing effects of the details in the image is minimized.



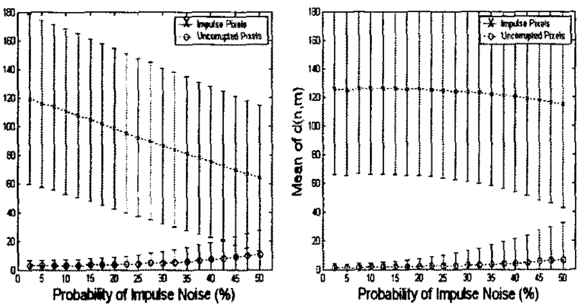
(a) (b) (c) (d)

Fig. 3. Test images: (a) Lena, (b) Pepper, (c) Bridge, (d) Boat.

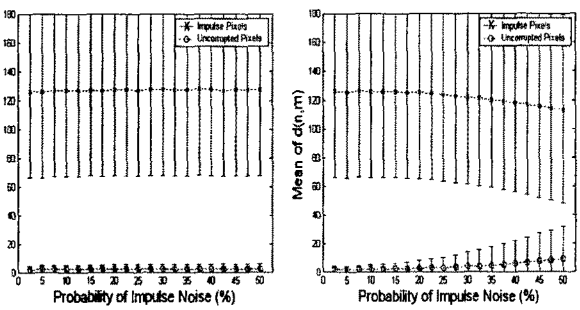
Figure 5 shows the noise detection results: the ratio of detected noisy pixels and the ratio of uncorrupted pixels which are identified as noise. Even when the noise level is as high as 30%, the proposed method can still identify most of the noisy pixels with fewer false detections. Compared with other techniques, the proposed method has highly robust, accurate performance of noise detection for the Pepper and

Bridge images corrupted by up to 50% of impulse noise.

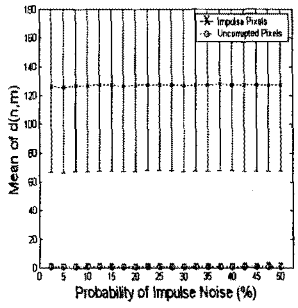
The effect of threshold value T_d on the performance of impulse noise detection is also studied. Figure 6 shows misclassification (undetected noises and falsely detected signals) ratio results of the Boat image by threshold T_d. Clearly the value of T_d depends on impulse noise ratio. The value of threshold T_d in the conventional methods should be decreased for high impulse noise ratio. However, good performance can be obtained with the proposed method using a single constant threshold value ($T_d \approx 20$). Therefore, comparing with other methods, the proposed method can distinguish more noise pixels with fewer misclassifications.



(a) (b)

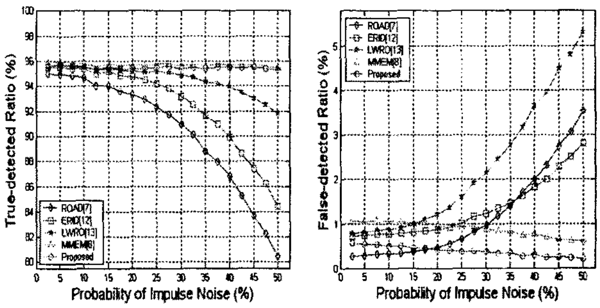


(c) (d)

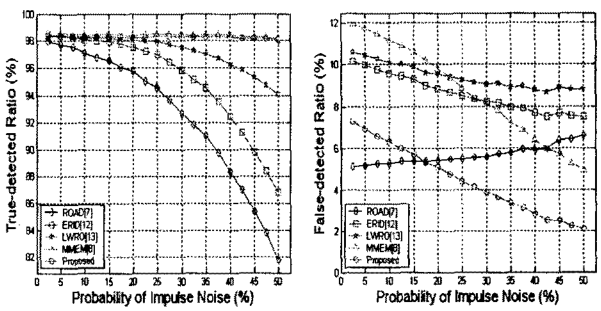


(e)

Fig. 4. Comparison of mean $d(n,m)$ values of impulses and uncorrupted pixels in the Lena image ($W=3$): (a) ROAD[7], (b) PSM[6], (c) MMEM[8], (d) LWRO[13], (e) Proposed.



(a)



(b)

Fig. 5. Comparison of noise detection results ($W=3$, $T_d=15$, $T_l=2$, $T_u=8$): (a) Pepper, (b) Bridge.

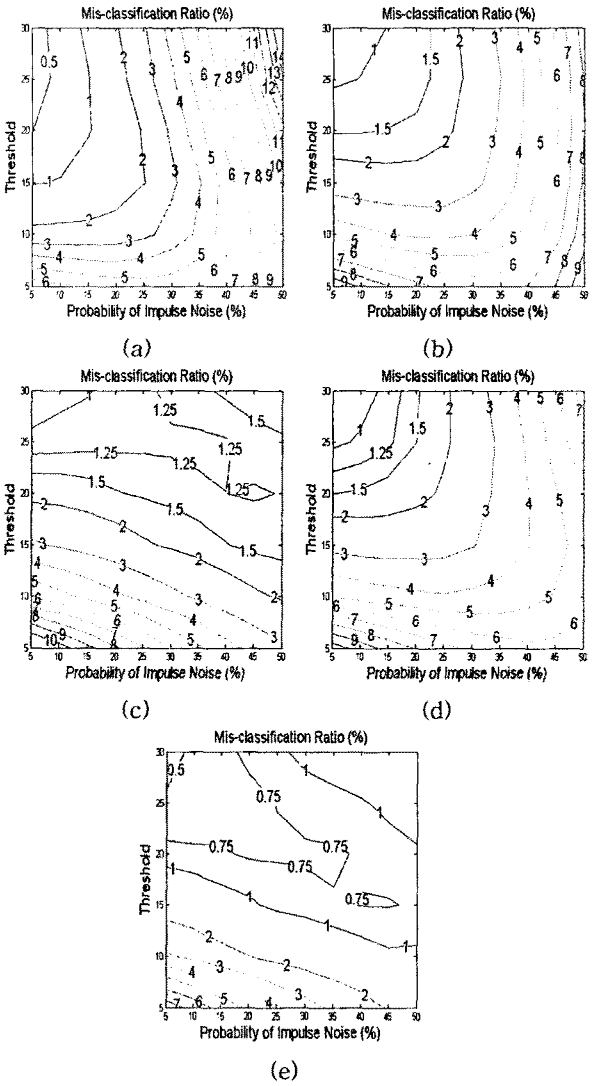


Fig. 6. Comparison of misclassification ratio results for the Boat image $W=3$, $T_l=2$, $T_u=8$): (a) ROAD[7], (b) ERID[12], (c) MMEM[8], (d) LWRO[13], (e) Proposed.

IV. Conclusions

In this paper, we present a new efficient impulse noise detection based on rank estimation, in which we can identify more noisy pixels with less misclassifications. Experimental results show that the proposed method produces better performance than many other well-known methods. The proposed detection is also robust to noise ratio, and can be used with any noise removal filter.

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