A Study on Image Restoration Algorithm in Random-Valued Impulse Noise Environment

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Abstract—Digital images are often corrupted by impulse noise, and it is very important to remove random-valued impulse noise. Cleaning such noise is far more difficult than cleaning salt and pepper impulse noise. In this paper, we proposed an efficient way to remove random-valued impulse noise from digital images. This novel method comprises two stages. The first stage is to detect the random-valued impulse noise in the image and the pixels are roughly divided into two classes, which are “noise-free pixel” and “noise pixel”. Then, the second stage is to eliminate the random-valued impulse noise from the image. In this stage, only the “noise pixels” are processed. The “noise-free pixels” are copied directly to the output image. Simulation results indicated that our method provides a significant improvement over many other existing algorithms.

Index Terms—Random valued impulse noise, noise detect, image restoration.

I. INTRODUCTION

DURING the acquisition or transmission, images are often corrupted by impulse noise. An important characteristic of this type of noise is that only parts of the pixels are corrupted and the rest are noise free. So it is very important to eliminate noise in images before subsequent processing, such as edge detection. There are many types of impulse noise. Let \( K(i,j) \) be the gray level of a true image at pixel location \((i,j)\) and \([n_{\min},n_{\max}]\) be the dynamic range of true image. Let \( X(i,j) \) be the gray level of the noisy image at pixel \((i,j)\), then

\[
X(i,j) = \begin{cases} 
R(i,j), & \text{with probability } r \\
K(i,j), & \text{with probability } 1-r
\end{cases}
\]

Where \( R(i,j) \in [n_{\min},n_{\max}] \) are random numbers and \( r \) is the noise ratio. For example, for salt and pepper impulse noise, noisy pixels take either \( n_{\min} \) and \( n_{\max} \). In this paper, we focus on general random-valued impulse noise where \( R(i,j) \) can be any numbers between \( n_{\min} \) and \( n_{\max} \). Cleaning random-valued impulse noise is more difficult than cleaning salt and pepper impulse noise, because salt and pepper impulse noise is only take either maximum or minimum value, but random-valued impulse noise can be any numbers between maximum and minimum.

Standard median (SM) filter has been widely used in removing random-valued impulse noise, where the output pixel is set to the median of the neighborhood pixels [1]. However, the standard median filter tends to modify not only noise pixels but also noise-free pixels. This will result the elimination of fine details such as thin lines and corner, blurring, or distortion in the images. In order to avoid distorting details, many other median filers were found, such as center weighted median (CWM) filter and switching median (SW) filter, and Min-max filter. Also the mean filter (MF) is one of the famous linear methods to remove impulse noise. However, when the observed images are highly corrupted by random-valued impulse noise, they are not enough to detect impulse noise. Thus, further improvement in the impulse detector is required for more accurate image restoration.

In this paper detail preserving filter for random-valued impulse noise removal is proposed. In the first, we analyze the noise candidates and classify them into noise-free pixels, noisy pixels. Finally, the process employed a modified nonlinear filter to remove the noise.

This paper is organized as follows. Section II reviews some conventional algorithms. Section III introduces the proposed algorithm for removing the random-valued impulse noise in the corrupted image, Section IV presents the experiments and the comparison results between the proposed algorithm and the other conventional algorithms. Finally we make a brief conclusion in Section V.

II. CONVENTIONAL ALGORITHM

2.1. Standard median filter

SM filter is the most important and popular nonlinear filter which exploits the rank-order information of pixel intensities within a filtering window and replaces the
center pixel with the median value [1]. Mask size can be defined as (1).

\[ W = \{(s,t) | -N \leq s \leq N, -N \leq t \leq N\} \]  

(1)

Here, \( (s,t) \) is the position of the pixels in the mask and the mask size is \((2N+1) \times (2N+1)\), and then SM filter chooses the median value in the mask.

\[ Y(i,j) = \text{med}\{X(i+s, j+t) | (s,t) \in W\} \]  

(2)

Where, \( X(i,j) \) is denoted as input value, \( Y(i,j) \) is the output value and \( \text{med}\{\} \) is denoted as median value.

2.2. Switching median filter

SW filter has been shown to be more effectively than uniformly applied filters. The impulse detection is the core technique in these filters that determines the quality of the filtered images. It is based on that the noise pixel value is substantially larger or smaller than its neighboring pixel values in the filtering window.

The standard median filter outputs the median value of the pixels in the window is \( \text{mid} \). The output of the switching median filter is given by:

\[ Y(i,j) = \begin{cases} 
\text{mid}, & \text{if } |\text{mid} - X(i,j)| > T_D \\
X(i,j), & \text{otherwise}
\end{cases} \]  

(3)

Where \( T_D \) is a fixed parameter. The numerical value of \( T_D \) is defined a prior or chosen after many practical tests.

2.3. Center weighted median filter

CWM filter, which gives more weight to the center pixel and other pixels in the window are given weight for \( 1 \). The output \( Y(i,j) \) of the CWM filter is given by

\[ Y(i,j) = \text{med}\{X(i+s, j+t), 2KX(i,j) | (s,t) \in W\} \]  

(4)

Here, \( 2K \) is the value of weight which is given to the center pixel in the filtering window.

2.4. Min-max filter

Min-max filter first assumes that the impulse is equally likely to be positive or negative, by definition of impulsive noise given earlier, min-max filter can improve the performance of median filters by first separating the input pixels. Min-max filter is given by

\[ Y(i,j) = \begin{cases} 
\max\{X(i+s, j+t) \} & \text{if } X(i,j) > \max\{X(i+s, j+t) \} \\
\min\{X(i+s, j+t) \} & \text{if } X(i,j) < \min\{X(i+s, j+t) \} \\
X(i+s, j+t) & \text{otherwise}
\end{cases} \]  

(5)

Min-max filter not only can remove impulse noise but also can preserve the details.

2.5. Mean filter

MF is a straightforward spatial-domain technique for image restoration. The procedure is to generate a smoothed image whose gray level at every point \((i,j)\) is obtained by averaging the gray level values if the pixels in the mask, which contained in a predefined neighborhood of \((i,j)\). Mean filter is denoted as (6).

\[ Y(i,j) = \frac{1}{Z \times Z} \sum_{i,j} X(i+s, j+t) \]  

(6)

\[ Z \in W, \ Z = 2N + 1 \]

Here, \( W \) is mask size.

III. PROPOSED METHOD

In order to preserve the edges and fine details, in this paper first detected noise from corrupted image, and the pixels are divided into noise and noise-free pixel. Only noisy pixel is replaced by filter output.

A. Impulse noise detection

In the proposed scheme, a sliding window centered around \( X(i,j) \) is employed to detect the extreme for the corrupted pixels. To find out impulse noise efficiently and preserve details, we proposed noise detection method contains with three stages. Fig. 1 is the \( 3 \times 3 \) filtering mask.

![Fig. 1. Filtering mask.](image)
Firstly, the classification of noise pixel is accord to the difference values of pixel’s neighborhood region. The image edge gray has continuity in one or several directions in the neighborhood region. But the noise points gray are discontinuous in most directions. It means if a pixel is impulse noise point, it has the maximum difference value in most direction [2].

In this paper, if the difference \((d_i)\) is larger than threshold \(T_1\) and the number \((N_p)\) which satisfies this situation is greater than the other threshold \(T_2\), then, the center pixel will be defined as impulse noise.

Secondly, maybe after the first stage to detect impulse noise there are also some noise pixels are missed. So second stage uses following method.

\[
g_d = \frac{\sum_{s=-N}^{N} \sum_{t=-N}^{N} [X(i + s, j + t) - X(i, j)]}{(2N + 1)^2 - 1}
\]

(7)

Where, \(g_d\) is the mean of the difference between eight neighborhood pixels and center pixel \(X(i, j)\). We also denoted the other variance \(g_y\) to compare with \(g_d\).

\[
g_y = \frac{\sum_{s=-N}^{N} \sum_{t=-N}^{N} [X(i + s, j + t) - X(i, j)]}{(2N + 1)^2}
\]

(8)

\[
\Delta g = |g_d - g_y|
\]

(9)

Here, \(\Delta g\) is the absolutely difference value between the \(g_d\) and \(g_y\). If the center pixel is noise-free pixel, the value of \(\Delta g\) is very small, but if it is noise pixel, \(\Delta g\)’s value maybe greater than one parameter’s value. So we identified a threshold to compare with \(\Delta g\), if the value of \(\Delta g\) is less than threshold \(T_3\), it means the center pixel of window is noise-free pixel, otherwise the pixel is noise.

Third, in the sliding window can be divided into four one-dimensional sub window, horizontal (H), vertical (V), main diagonal (MD) and auxiliary diagonal (AD) detections. The Fig. 2 shows the four detections. The gray dot is the center pixel \(X(i, j)\) and black dots are the two pixels to be used in following calculating. In each sub window, the sum of absolute value of difference between \(X(i, j)\) and the other pixel is denoted as \(v_1, v_2, v_3, v_4\).

The \(v_1, v_2, v_3, v_4\) can be expressed as following:

\[
\begin{align*}
  v_1 &= |2X(i, j) - X(i, j-1) - X(i, j+1)|; H \\
  v_2 &= |2X(i, j) - X(i-1, j) - X(i+1, j)|; V \\
  v_3 &= |2X(i, j) - X(i-1, j-1) - X(i+1, j+1)|; MD \\
  v_4 &= |2X(i, j) - X(i+1, j-1) - X(i-1, j+1)|; AD
\end{align*}
\]

(10)

\[
v = \min[v_1, v_2, v_3, v_4]
\]

(11)

Condition (11) denotes that \(v\) represents the minimum of \(v_1, v_2, v_3, v_4\). Then if \(v > T_4\), the center pixel of the window also be treated as impulse noise.

So, the noise detection can be expressed in the form:

\[
X(i, j) \in \begin{cases} 
  \text{Noise} & \text{if } d_i > T_1 \text{ and } N_p > T_2 \\
  \text{or if } \Delta g > T_3 \\
  \text{or if } v > T_4 \\
  \text{Noise-free} & \text{otherwise}
\end{cases}
\]

(12)

B. Impulse noise filter

After detecting the noise pixel, it is very important to choose fixed method to remove noise from image. Though the conventional filters can remove the impulse noise effectively, but they can’t preserve image details. This will result the elimination of fine details such as thin lines and corner, blurring, or distortion in the images [2]. Therefore, this paper proposed more efficient modified nonlinear filter. This paper proposes the following function of the weighted value:

\[
y = \frac{1}{1 + z^2}
\]

(13)
The calculation process of the weighted values is described as follows:

\[ m = X(i + s, j + t) - \text{mid} \]  \hspace{1cm} (14)

Here, \( \text{mid} \) is the median value of the window \( W \).

\[ M = \sum_{s=-N}^{N} \sum_{t=-N}^{N} \frac{1}{1 + m^2} \]  \hspace{1cm} (15)

And weight value can be denoted as (16).

\[ w(i + s, j + t) = \frac{1}{(1 + m^2) \times M} \]  \hspace{1cm} (16)

The noise pixel is changed as (17).

\[ p(i, j) = \sum_{s=-N}^{N} \sum_{t=-N}^{N} X(i + s, j + t) \times w(i + s, j + t) \]  \hspace{1cm} (17)

To make the output value is similar to the original pixel’s value, let mean of \( \text{mid} \) and \( p(i, j) \) as the output value. The output after filtering is:

\[ Y(i, j) = \frac{1}{2} [\text{mid} + p(i, j)] \]  \hspace{1cm} (18)

The structure of the proposed algorithm is shown Fig. 3.

**IV. EXPERIMENT RESULT ANALYSES**

The proposed algorithm is tested using 512×512 standard images such as Peppers image (Gray). For comparison, we also test the SM filter, the SW filter, the CWM filter, the Min-max filter and the MF. We employ the peak signal to noise ratio (PSNR) to illustrate the quantitative quality of the reconstructed image for various methods.

Fig. 4 shows the simulation result of the Peppers image which corrupted by random-valued impulse noise is restored by conventional algorithms and proposed algorithm.

**Fig. 3. Structure of the proposed algorithm.**

**Fig. 4. Simulation result of Peppers image.**

(a) Test image  (b) Noisy image  (c) SM (3×3)
(d) SW (3×3)  (e) CWM (3×3,C=3)
(f) Min-max (3×3)  (g) MF (3×3)
(h) Proposed filter
In the Fig. 4, (a) is the original image; (b) is the noisy image that corrupted by random-valued impulse noise with the density of P=20%. (c) ~ (h) show the result of restoration by SM (3×3) filter, SW (3×3) filter, CWM (3×3,C=3) filter, Min-max (3×3) filter, MF (3×3) and the proposed method respectively.

Visual comparison among these filtered images show that too much noise remains in the images filtered by the SW filter and Min-max filter. Although the SM filter, CWM filter and MF filter perform better in noise suppression than the SW filter and Min-max filter, they still remains certain amount of noise in the filtered image and they damage some details in the image to a certain extent. As a result these filters blur the image edges. However, proposed filter not only suppress the impulse noise very effectively but also preserves the details in the images very well.

Fig. 5 compares the noise removal results by changing the random-valued impulse noise density with 5%~50%. From Fig. 5, proposed method performs better than conventional algorithms, especially well at low density noise environment.

Fig. 5. PSNR with variation of Impulse Noise.

Table 1 lists the PSNR values of restored images with P=10%, 20%, 30%, 40% or 50% for Peppers image. The proposed method performs the best PSNR in the corrupted image.

<table>
<thead>
<tr>
<th>P/%</th>
<th>SM 3×3</th>
<th>SW 3×3</th>
<th>CWM 3×3</th>
<th>Min-max</th>
<th>MF 3×3</th>
<th>Proposed</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>33.54</td>
<td>21.25</td>
<td>34.67</td>
<td>24.84</td>
<td>26.15</td>
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<td>18.20</td>
<td>29.71</td>
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<td>30</td>
<td>27.38</td>
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<td>16.65</td>
<td>20.63</td>
<td>28.64</td>
</tr>
<tr>
<td>40</td>
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<td>21.39</td>
<td>22.30</td>
<td>14.76</td>
<td>18.90</td>
<td>24.54</td>
</tr>
<tr>
<td>50</td>
<td>20.51</td>
<td>18.62</td>
<td>19.51</td>
<td>13.30</td>
<td>17.43</td>
<td>21.15</td>
</tr>
</tbody>
</table>

V. CONCLUSIONS

In this paper, a new algorithm is proposed to remove random-valued impulse noise in the images, which employs the three stages impulse noise detection and the modified nonlinear filter. The experimental results demonstrate that our design achieves excellent performance in terms of quantitative evaluation and visual quality in low noise ratio. The proposed method is superior to traditional algorithms and has good capability in random-valued impulse noise suppression, and can reserve image details.

REFERENCES


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