LJ-011

Efficient Impulse Detection for Image Restoration
–Application of Highly Corrupted Images due to Fixed-valued and Random-valued Impulse Noise–

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1. Introduction

Impulse noise is often caused by errors during image acquisition or transmission through communication channels. Hence, suppression of impulse noise is one of the important tasks in image restoration. Several nonlinear filters have been proposed for the restoration of images corrupted by impulse noise [1]. One of these filters is the median filter, which can successfully remove impulse noise from the observed images while preserving the edges. However, the median filter tends to modify not only noisy pixels but also undisturbed good pixels, which should not be modified. As a result, observed images cannot be restored accurately.

In order to avoid distorting good pixels, several switching schemes have been proposed [2]-[7]. These schemes consist of two parts: the first part is an impulse detector which determines the location of impulse noise, and the second part is a noise reduction filter which modifies only the pixels determined to be impulse noise by the first part. With a switching scheme, impulse detection is crucial because its results are utilized for subsequent noise reduction filtering. However, when the observed images are highly corrupted, the performances of the conventional impulse detection methods [2]-[7] are not enough to thoroughly detect impulse noise.

Thus an impulse detection method using two systems has been proposed in [8] to accurately detect impulse noise even in highly corrupted images. The method successfully detects fixed-valued impulse noise more than the other methods. However, it poorly detects random-valued impulse noise because the second system in [8] is formulated with the assumption that the measurement noise is in fact fixed-valued impulse noise. Thus this paper proposes a novel impulse detection method, which introduces a new second system using another assumption independent of the type of noise. By introducing this new second system, the proposed method can accurately detect not only fixed-valued but also random-valued impulse noise even in highly corrupted images. The efficiency of the proposed method has been verified through experiments.

2. Impulse Noise Models

Two well-known impulse noise models are the fixed-valued and the random-valued impulse noise models. The fixed-valued impulse noise model is defined by using the following probability p_f:

$$x(i, j) = \begin{cases} z(i, j) & \text{with probability } 1 - p_f \\ d & \text{with probability } p_f \end{cases} \quad (1)$$

where $z(i, j)$ and $x(i, j)$ denote the gray-levels at location (i, j) of the original image and the observed image, respectively. The noise value d is equal to 0 or the maximum gray-level.

The random-valued impulse noise model is defined with the following probability p_r:

$$x(i, j) = \begin{cases} z(i, j) & \text{with probability } 1 - p_r \\ s(i, j) & \text{with probability } p_r \end{cases} \quad (2)$$

The noise value $s(i, j)$ is uniformly distributed from 0 to the maximum gray-level.

3. Previous Impulse Detection Methods

With a switching scheme, impulse detection is crucial to subsequent noise reduction filtering. However, the conventional impulse detection methods [2]-[7] have the following two problems:

(**Problem 1**) The first problem is that noisy pixels may not be detected, especially those that exist in flat areas. These pixels are called *undetected pixels* and remain in the restored images because they were not removed by the noise reduction filter.

(**Problem 2**) The second problem is that good pixels, especially those which are found in edge areas, may be misjudged as noisy pixels. These pixels are called *mis-detected pixels* and are modified by the noise reduction filter even though they are good pixels. Consequently the restored image includes over-smoothing, especially, in the edges.

Conventional impulse detection methods tend to increase the number of undetected and mis-detected pixels when the observed images are highly corrupted. Thus the impulse detection method in [8] has been proposed, which can reduce the number of both undetected and mis-detected pixels greater than the other methods even in highly corrupted images by using the following two systems:

System 1: Impulse detection based on an edge flag image. The undetected pixels and the mis-detected pixels occur in flat and edge areas, respectively. Therefore, in this system, a new flag image is introduced, named the edge flag image, which is an index used to classify the pixels of an observed image into two types: the pixels being in the flat areas and those in the edge areas. The pixels classified into the edge flag image areas are separately processed by using two median filters with different sizes of windows. By using a different window size for each area, System 1 can reduce the number of both undetected and mis-detected pixels more than the other methods.

System 2: Verification of the impulse detection result by System 1. When the observed images are highly corrupted, it is difficult to prevent undetected and mis-detected pixels by using only System 1. Therefore, in order to ensure the accuracy of System 1, System 2 was proposed, which verifies the impulse detection results by System 1. As the fixed-valued impulse noise has two values, being equal to 0 (negative) or the maximum gray-level (positive), System 2 was realized by using a property whereby the difference between any negative impulse noise or the difference between any positive impulse noise is equal to 0.

By using the combination of these two systems, the method in [8] can accurately detect fixed-valued impulse noise even in highly corrupted images. However, the method poorly detects random-valued impulse noise, because System 2 is formulated with the assumption that the measurement noise is fixed-valued impulse noise. Thus, to successfully detect not only fixed-valued impulse noise but also random-valued impulse noise, the proposed method introduces a new second system using another assumption independent of the type of noise. By introducing this new

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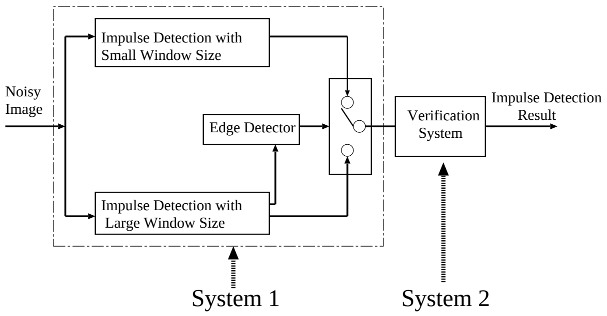

Figure 1: A new impulse detection method

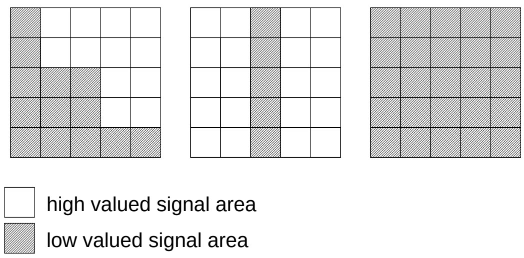

Figure 2: An example of signal areas in original images.

second system, the proposed method can successfully detect both types of impulse noise even in highly corrupted images.

4. Proposed Impulse Detection Method

In order to detect not only fixed-valued impulse noise but also random-valued impulse noise, the proposed method introduces a new second system, since the performance of System 2 in [8] is not sufficient for the above application.

In the proposed method, both System 1 in [8] and the new second system, being a verification system, are used as shown in Fig. 1. Let us explain the procedures of the verification system in the following section.

4.1 Verification System

In order to reduce the number of mis-detected pixels by System 1, only noisy pixels located in the edge areas are verified by a new system, since the mis-detected pixels mainly exist in the edge areas.

The new verification system is realized by using an assumption independent of the type of noise. The assumption is that an original image gradually varies in the signal area which consists of similar intensities, as shown in Fig. 2. That is, if the differences between intensities of the target pixel and its neighbors detected as good pixels are very similar, we can determine that the target pixel is a good pixel; otherwise, the target pixel is a noisy pixel. As a result, the verification system works as follows:

1. A target pixel at (i, j) is selected from the pixels with $f_{\text{noise}}(i, j) = 1$ and $F_{\text{edge}}(i, j) = 1$ obtained by System 1. The binary image f_{noise} denotes that $f_{\text{noise}}(i, j) = 1$ means a pixel at (i, j) is impulse noise ; $F_{\text{edge}}(i, j) = 1$ denotes a pixel in the edge areas.

2. As shown in Fig. 2, the pixels at (s, t)'s $(1 \le s \le W, 1 \le t \le W,\ (s, t) \ne (i, j))$ whose intensities are similar to the intensity of the target pixel are selected from the pixels within a $W \times W$ (W is an odd integer) window as follows:

$$f_{\text{area}}(s, t) = \begin{cases} 1 & \text{if } |g(i, j) - g(s, t)| < T_{\text{area}} \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

where $g(i, j)$ (or $g(s, t)$) is the result by obtained an iterative median filter; T_{area} is an integer which satisfies $0 \le T_{\text{area}} \le G$; G is the maximum gray-level. The binary image f_{area} denotes $f_{\text{area}}(s, t) = 1$ means signal area similar to that of the target pixel, as shown in Fig 2.

3. By using the binary image f_{area} obtained in procedure 2, the good pixels to be compared with the target pixel at (i, j) are selected from the pixels which satisfy the following equation:

$$f_{\text{pix}}(s, t) = \begin{cases} 1 & \text{if } |x(s, t) - g(s, t)| < T_{\text{pix}} \\ & \quad \text{and } f_{\text{area}}(s, t) = 1 \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

where T_{pix} is an integer which satisfies $0 \le T_{\text{pix}} \le G$; $f_{\text{pix}}(s, t) = 1$ denotes that a pixel at (s, t) should be compared with the target pixel at (i, j).

4. The intensity of the target pixel at (i, j) is denoted by $x(i, j)$ and the intensities of the pixels with $f_{\text{pix}}(s, t) = 1$ obtained by procedure 3 are denoted by $y(s, t)$'s; we compute the difference $|x(i, j) - y(s, t)|$ and the average u_R of the M smallest values is calculated.

5. If $u_R < T_R$; $0 \le T_R \le G$, then the verification system judges that the target pixel is a good pixel. Otherwise, the target pixel is judged to be a noisy pixel. Consequently, the impulse detection result obtained by System 1 is refined by the verification system as follows:

$$F_{\text{noise}}(i, j) = \begin{cases} 0 & \text{if } f_{\text{noise}}(i, j) = 1, F_{\text{edge}}(i, j) = 1 \\ & \quad \text{and } u_R < T_R \\ 1 & \text{if } f_{\text{noise}}(i, j) = 1, F_{\text{edge}}(i, j) = 1 \\ & \quad \text{and } u_R \ge T_R \\ f_{\text{noise}}(i, j) & \text{if otherwise} \end{cases} \tag{5}$$

where $F_{\text{noise}}(i, j)$ records the location of impulse noise; $F_{\text{noise}}(i, j) = 1$ (0) denotes that a pixel at (i, j) is (not) impulse noise.

Consequently, by introducing the verification system, our proposed method can detect not only fixed-valued but also random-valued impulse noise more accurately than the other methods even in highly corrupted images.

5. Experiments

In order to verify the high performance of the proposed method as a preprocessor for noise reduction filtering, experimental results are shown in Fig. 3, where each 128×128 square is extracted from an image whose size is 256 × 256 pixels and the maximum gray-level is 255. Figure 3(a) shows "lena" corrupted with 30% random-valued impulse noise. The random-valued impulse noise is uniformly distributed from 0 to 255. Figure 3(b) shows the restored image obtained by using the impulse detection results of the proposed method as a preprocessor for noise reduction filtering. For comparison, Fig. 3(c) and Fig. 3(d) are obtained by applying the impulse detection methods in [7] and in [8] as preprocessors for the noise reduction filtering, respectively.

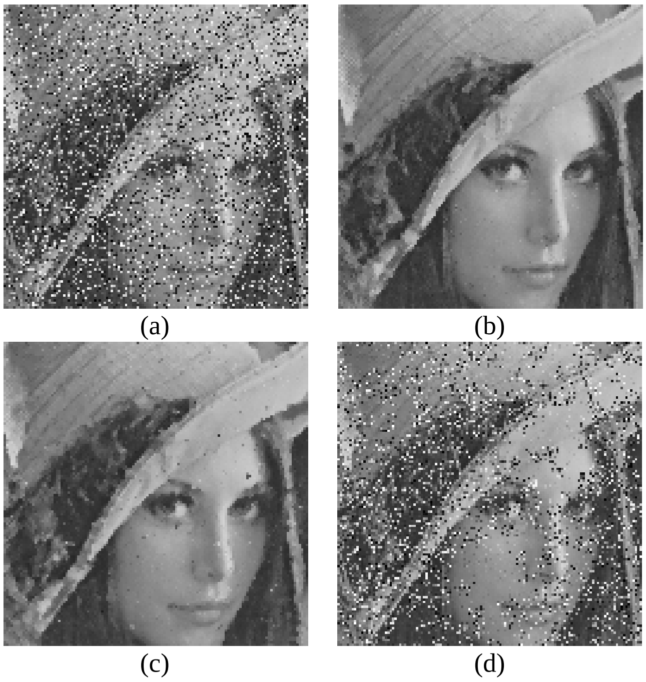

Figure 3: Image restoration results. (a) is corrupted “lena” by 30% random-valued impulse noise. (b) The proposed method; (c) The impulse detection method in [7]; and (d) The impulse detection method in [8], are used as preprocessors for the noise reduction filtering, respectively.

The noise reduction filtering is performed by the PSM filter [6], which is well known for its effectiveness. As shown in Fig. 3, it is clear that the noise reduction filtering using the proposed method can remove the random-valued impulse noise more accurately than the other impulse detectors.

Furthermore, the proposed method is applied to three corrupted images with fixed-valued or random-valued impulse noise, whose original images are “lena,” “bridge,” and “peppers” (256×256 pixels, 8bits/pixel gray scale images). For the fixed-valued impulse noise, the impulse noise takes on the values of 0 or 255. In contrast, for the random-valued impulse noise, the impulse noise is uniformly distributed from 0 to 255. The SNR’s of the restored images obtained by using the proposed method as a preprocessor for noise reduction filtering are shown in Table 1. For comparison, the SNR’s of the restored images obtained by using the impulse detection in [7] and in [8] as preprocessors for the noise reduction filtering are also shown. The noise reduction filtering is performed by the PSM filter. From Table 1, showing all results, the noise reduction filtering using the proposed detection method can restore the impulse noise corrupted images more accurately than both the impulse detection in [7] and in [8]. Especially, when the observed images are highly corrupted, the SNR’s of the restored images obtained by using the proposed method are much better than the other methods for both fixed-valued and random-valued impulse noise.

6. Conclusion

This paper has presented an accurate impulse detection method for the restoration of images corrupted by impulse noise. The simulation results demonstrate that the proposed method consistently provides satisfactory results of images highly corrupted by not only fixed-valued but also random-valued impulse noise. The experiments show the performance of the proposed method is much higher than other previous methods. This proposed method can be applied to

Further our proposed method will be improved to remove impulse noise from not only gray-scale images but also color images in the future.

Table 1: SNR’s (dB) of the restoration results. The corrupted images are fixed-valued and random-valued impulse noise, whose probability is 10% and 40%.

Image	Prob.	Type of impulse	Proposed method	Ref. [7]	Ref. [8]
lena	10%	Type 1[a]	29.34	28.73	29.10
		Type 2[b]	27.38	27.34	18.02
	40%	Type 1	21.50	14.44	21.36
		Type 2	22.14	20.20	9.02
bridge	10%	Type 1	24.03	23.43	24.38
		Type 2	22.17	21.84	13.33
	40%	Type 1	16.78	12.72	16.70
		Type 2	17.45	15.97	6.89
peppers	10%	Type 1	22.33	21.69	22.90
		Type 2	22.67	21.43	16.27
	40%	Type 1	18.12	13.77	18.25
		Type 2	19.19	17.48	8.23

[a] fixed-valued impulse noise
[b] random-valued impulse noise

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