PEER REGION DETERMINATION BASED IMPULSIVE NOISE DETECTION

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ABSTRACT

A peer region determination (PRD) algorithm for impulsive noise detection in digital image is proposed that removes random-valued impulsive noise while preserving very fine image details. This algorithm determines the peer region for each pixel adaptively by finding the variation of pixel values in a 5×5 filter window. If the number of member pixels in the peer region is very small, the pixel being processed is thought to be isolated from other pixels and thus considered as an impulsive noise. In addition, this noise detector can be easily modified to perform feature selective filtering. Experimental results show that the proposed noise detection algorithm outperforms other existing non-linear filters and adaptive noise detection based filters in noise removal and image details preservation. Finally, the concept of the PRD algorithm applied on other image processing applications is discussed.

1. INTRODUCTION

In digital image, pixels are often corrupted by impulsive noise due to fault in image acquisition device, undesired acquisition conditions or errors encountered in image transmission. Impulsive noise is very noticeable by human eyes and it can cause serious errors in some image processing applications. As a result, impulsive noise removal is often performed as preprocessing steps for other image processing systems like image quantization. Various impulsive noise removal algorithms have been proposed in the past years and their objective is to remove the impulsive noise while preserving image details. However, they always possess contradiction. Some typical non-linear filters like median filter [1] and center weighted median filter [1] can remove most of the impulsive noises but they also remove lots of image details. Some noise detection based adaptive filters such as Lee's algorithm [2], $\mathrm{IND}_{\mathrm{MASK}}$ [3] and SD-ROM [4] can do better as they filter only the pixels which are detected to be noise. As a result, pixels detected as noise-free will not be affected. However, for some image details like a fine straight line, they will probably be detected as noise in the above algorithms. In these algorithms, the noise detection process for each pixel is done in a 3×3 window. In fact the information obtained from the eight neighbor pixels in the window is not enough for detecting the noise accurately even by human eyes. The insufficiency in information eventually causes errors in noise detection.

In the proposed algorithm, a 5×5 filter window is used to process each pixel and a peer region will be determined for each of them. Inside the peer region, all member pixels are connected together and they are similar to the center pixel with respect to the variation of pixels in the window. Finally, the member size of the peer region can be used to judge the corruptness of a pixel. Experiments conducted with other five algorithms show that the proposed algorithm can efficiently remove random-valued impulsive noise while keeping image details unaffected.

2. IMPULSIVE NOISE DETECTION

Let the center pixel in a 5×5 window being processed be $x_{0,0}$ and pixel at position (*i, j*) of the window be $x_{i,j}$ where $-2 \le i \le 2, -2 \le j \le 2$. The 5×5 window is divided into three shells of one pixel thick. These are the innermost shell, which consists of the center pixel only, denoted as S_0, the middle shell S_1 and the outermost shell S_2.

2.1. Peer Region Determination

The purpose of peer region determination is to find out similar neighbor pixels for each pixel. One approach in doing this is to set a threshold K, such that any $x_{i,j}$ satisfying $|x_{0,0} - x_{i,j}| \le K$ will be regarded as similar to $x_{0,0}$. However, thresholds used in the typical existing algorithms are not robust enough to detect impulsive noise while preserving highly-detailed image content. For example, Lee's algorithm [2] applies Weber's law [5], which considers the average intensity of neighbor pixels, as an adaptive threshold to process each pixel. However, in dark area, sharp changes in uncorrupted image will be detected as noise easily.

To determine the peer region in a 5×5 window, the variation of pixel values are examined and member pixels are identified. Let the variation be neighbor variation v, defined by the average of absolute difference between all pixels inside the window and their mean. i.e.,

$$v = \frac{1}{25}\sum_i \sum_j |x_{i,j} - \mu|\,, \quad -2 \le i \le 2, -2 \le j \le 2$$

where

$$\mu = \frac{1}{25}\sum_i \sum_j x_{i,j}\,, \quad -2 \le i \le 2, -2 \le j \le 2$$

This neighbor variation v is determined locally for each pixel. For a highly-detailed area (with sharp changes in content), the variation in pixel values is large and results in a large v. For a flat area, the variation in pixel values is small and results in a small v. However, since v will be too small in flat area and this can contribute error in noise detection, a lower bound have to be set for v. Here, Weber's law [5] is applied as the lower bound. i.e.,

$$v = \max\{v, \alpha + \log_2(\mu)\}$$

where α is the lowest limit for detecting impulsive noise.

With the neighbor variation v calculated locally, the peer region formed by pixels in the window can be determined. To record the location of the peer region in the 5×5 window, a 5×5 zero matrix R (region map) is used. $R_{i,j} = 1$ implies the pixel at position (i, j) of the window is in the peer region. By definition, the center pixel $x_{0,0}$ is in the peer region and thus we set $R_{0,0} = 1$. To determine the peer region, we first check whether the pixels in S_1 are similar to $x_{0,0}$. The result is recorded as

$$R_{i,j} = 1 \ \text{ if } |x_{0,0} - x_{i,j}| \leq v \times \beta$$

where $x_{i,j} \in S_1$ and β controls the sensitivity of the noise detector. Then, we check whether the pixels in S_2 are in the peer region. The method is to compare the similarity of each pixel in S_1 with the corresponding three outer adjacent pixels in S_2 (e.g. outer adjacent pixels of $x_{1,1}$ are $x_{1,2}$, $x_{2,1}$ and $x_{2,2}$). But there is a prerequisite that the pixel of S_1 should be in the peer region before its adjacent pixels in S_2 can be regarded as in the peer region. This ensures all member pixels in the peer region are connected together and so there is no isolated '1' inside R. For instance, we check and record whether the three outer adjacent pixels of $x_{1,0}$ are in the peer region by

$$R_{i,j} = 1 \ \text{ if } |x_{1,0} - x_{i,j}| \leq v \times \beta \text{ and } R_{1,0} = 1$$

where $i = 2, -1 \leq j \leq 1$. As a result, pixels similar to $x_{0,0}$ inside the processing window are connected to form a peer region as the '1's in region map R.

2.2. Impulsive Noise Determination

To decide whether $x_{0,0}$ is an impulsive noise, we define an impulsive noise as a pixel which is very isolated from other background pixels in the same window and this can be determined by the member size of its peer region. If the member size is smaller than or equal to a threshold T, the center pixel will be regarded as noise. For slightly corrupted images, the chance for impulsive noises to cluster together is small and a small T $(e.g.\ 2)$ can be used. Similarly, a large T $(e.g.\ 5)$ can be used for highly corrupted images. The detection of noise with this threshold T puts no constraint on the shape of the impulsive noises. However, if we constrain the shape of the peer region, the properties of the noise detector can be varied to become a feature selective filter for some specific applications. For example, if the shape of the formed peer region is exactly a horizontal line of one pixel thick across the 5×5 window, the pixels in the line can be regarded as noise and filtered. Then this noise detector becomes a missing line noise detector.

In typical digital images, there will be very fine image details which may be just one pixel thick. However, in Lee's algorithm [2], it detects noise by using the idea that edges generally have more than three similar pixels inside the 3×3 window. This will probably remove the very fine image details. In the proposed algorithm, there is no restriction put on the shape of the peer region. Even there is just one pixel of S_1 is in the peer region, the center pixel will not be detected as noise if the peer region has member size larger than the threshold T. As a result, fine image details can be preserved. Moreover, in the IND_{MASK} algorithm [3], it uses eight masks to check for the three most similar edge pixels in one of the eight directions. This noise detection algorithm is thus directional. However, the edge of an image is not always confined in a particular direction, so the use of these eight masks has deficiency in noise detection. In the proposed algorithm, the determination of peer region is nondirectional. So the detection of noise is more complete and accurate.

2.3. Hidden Impulsive Noise Removal

In the PRD algorithm described above, center pixel in a peer region with member size larger than the threshold T will not be detected as impulsive noise. However, some impulsive noises may be hidden by sticking to the edge of object inside an image and cannot be detected. In such a case, the center noisy pixel is not part of the edge, but it is very similar to the edge pixels adjacent to it. As a result, the PRD algorithm regards them as in a peer region and failed to detect it as noise by checking the member size with threshold T. Therefore, we have to remove these hidden noises by another method. Some graphical examples of the hidden noise are shown in Fig. 1 below. For each window in Fig. 1, the center pixel is the hidden noise and other shaded pixels are the edge.

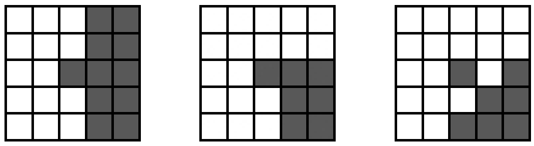

Fig. 1. Samples for hidden impulsive noise.

The region map R of a hidden impulsive noise has certain properties that allow us to distinguish it from the other noise-free pixels. Firstly, the number of member pixels of the peer region in the middle shell should be smaller than or equal to three. This property is valid because the hidden noise is just sticking to the edge of some objects but not on the edge. Secondly, in the original uncorrupted image, the center pixel should be very different from the middle shell pixels in the peer region. It is obvious because the original uncorrupted center pixel is not part of the edge. To summarize, the steps to detect and remove hidden impulsive noise are as follows:

1. For all center pixels $x_{0,0}$ that passed the test with threshold T, find out candidate hidden noisy pixel if its R satisfies

$$\sum_i \sum_j R_{i,j} \leq 3, \quad \text{where } -1 \leq i \leq 1, -1 \leq j \leq 1 \text{ and } i \neq j \text{ when } i = 0 \text{ or } j = 0$$

2. Approximate the pixels of the uncorrupted image by filtering the corrupted pixels with a median filter of 3×3 cross window and denote this filtering operation as $Median(\ )$. For center pixels $x_{0,0}$ satisfy point 1 above, calculate the minimum absolute difference d defined by

$$d = \min\{|Median(x_{0,0}) - Median(x_{i,j})| : x_{i,j} \in S_1 \text{ and } R_{i,j} = 1\}$$

A threshold D is used as an upper bound for d (empirically, $D = 20$). For $d \geq D$, the pixel $x_{0,0}$ is regarded as an impulsive noise because it is similar to its neighbor pixels in the corrupted image but not in the approximated original image. Finally, the detected hidden noise is replaced by $Median(x_{0,0})$.

3. EXPERIMENTAL RESULTS

To test the performance of the proposed noise detection algorithm for impulsive noise removal, non-linear filters including median filter of 3×3 square window [1], Fast Impulsive Noise Removal

[6] and noise detection based adaptive filters including Lee's algorithm [2], IND_{MASK} [3], SD-ROM [4] are used for comparison. To emphasize the detail preserving ability of the proposed algorithm, we used images with very fine image details in doing the simulations. They are the "Clock" and "Boat" 8-bit images with size 256×256 as shown in Fig. 2. Different percentages

(a)"Clock" (b) "Boat"

Fig. 2. Two test images.

of random-valued impulsive noise are added to them in the simulations. The following criteria are used for comparing the algorithms:

1. Peak Signal to Noise Ratio (PSNR) in dB
2. Mean Absolute Error (MAE)
3. Removal ratio η_r defined by

$$\eta_r = \frac{no.\ of\ correclty\ detected\ impulsive\ noises}{total\ no.\ of\ impulsive\ noises}$$

Preservation ratio η_p defined by

$$\eta_p = \frac{no.\ of\ correclty\ detected\ impulsive\ noises}{total\ no.\ of\ detected\ impulsive\ noises}$$

Efficiency of the noise detector η_d defined by

$$\eta_d = \eta_r \times \eta_p$$

To use the proposed noise detection algorithm for impulsive noise removal in the simulations, the sensitivity of the noise detector is set to $\beta = 1.2$ and median filter of 3×3 square window is used for filtering the detected impulsive noise with peer region of member size smaller than or equal to three $(i.e.\ T = 3)$. Once a noisy pixel is detected, it is filtered immediately before shifting the window to process the next pixel.

In Table 1 and Table 2, the simulation results of the "Clock" and "Boat" images corrupted by 1%, 5% and 10% random-valued impulsive noise are shown. The "None" rows indicate the results without any noise removal. When an image is slightly corrupted by impulsive noise, most of the original image details are not corrupted. Such an image is good for testing the edge preserving ability of the noise removal algorithms. In Table 1, the "Clock" image is slightly corrupted by 1% of noise. We can see that the preservation ratio η_p of the proposed algorithm is much higher than other algorithms (50% higher than the second high η_p). This indicates the proposed algorithm is very accurate in noise detection and it can preserve most of the image details. In Fig. 3, the edge preserving ability of the proposed algorithm is illustrated. Part of the denoised "Clock" image with fine details is shown. Readers can look at the three numbers on the clock and realize that the proposed algorithm can remove the impulsive noise without much destruction to image details. For the removal ratio η_r, it is not very high for all algorithms except median filter because some of the random-valued impulsive noises are very similar to the background and they cannot be detected even by human eyes. Besides, the PSNR and MAE of the proposed algorithm are shown to be better than the other five algorithms even simple median filter is used for noise filtering. If filter with adaptively selected windows in [3] is used instead, the PSNR and MAE are possible to have further improvements.

4. CONCLUSIONS AND FUTURE WORK

In this paper, a random-valued impulsive noise detection algorithm based on peer region determination is proposed and analyzed. Variation of pixel values in the 5×5 window is used to determine the peer region for each pixel and then noise detection is based on the peer region. Experimental results show the proposed algorithm is good at impulsive noise removal and its image details preservation ability is much better than other existing impulsive noise removal algorithms.

The concept of finding similar pixels in a filter window used in the PRD algorithm is also used in [7]. In [7], the peer group is formed by neighbor pixels with the closest intensity to center pixel and the member size of the peer group is determined by Fisher's discriminant. The objective of peer group in [7] is very similar to the peer region proposed in this paper. However, the definition and properties of the peer region are quite different from the peer group as it requires all its members are connected together in the region and the member size is determined by using the variation of pixel values which has lower complexity than calculating the Fisher's discriminant. In this paper, the PRD algorithm uses a 5×5 filter window for impulsive noise detection, but the size of window can be varied to cater for different applications. By applying and elaborating the concept of this PRD algorithm, more image processing applications can be developed like image smoothing, spatial image classification and image quantization in [7]-[9] respectively.

5. REFERENCES

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	1% Noise Level					5% Noise Level					10% Noise Level				
	PSNR	MAE	η_r	η_p	η_d	PSNR	MAE	η_r	η_p	η_d	PSNR	MAE	η_r	η_p	η_d
Proposed PRD	39.98	0.21	0.79	0.84	0.67	34.76	0.54	0.77	0.96	0.75	31.54	1.00	0.75	0.97	0.73
Median Filter	29.47	2.67	1.00	0.01	0.01	28.99	2.89	1.00	0.05	0.05	28.21	3.20	1.00	0.10	0.10
Fast Removal	38.27	0.34	0.90	0.14	0.13	27.05	1.53	0.80	0.42	0.38	22.80	3.71	0.72	0.61	0.44
Lee's algorithm	28.46	0.84	0.73	0.33	0.24	27.30	1.23	0.74	0.70	0.52	27.40	1.67	0.73	0.82	0.59
$\mathrm{IND}_{\mathrm{MASK}}$	34.33	1.12	0.72	0.56	0.40	32.43	4.36	0.72	0.86	0.62	30.82	0.71	0.71	0.92	0.65
SD-ROM	27.52	1.83	0.87	0.41	0.36	27.21	5.34	0.86	0.76	0.65	27.20	9.61	0.86	0.87	0.75
None	27.02	1.03	-	-	-	20.23	4.64	-	-	-	17.35	9.07	-	-	-

Table 1. Restoration of the "Clock" image corrupted by 1%, 5% and 10% random-valued impulsive noise.

	1% Noise Level					5% Noise Level					10% Noise Level				
	PSNR	MAE	η_r	η_p	η_d	PSNR	MAE	η_r	η_p	η_d	PSNR	MAE	η_r	η_p	η_d
Proposed PRD	40.73	0.22	0.73	0.79	0.58	34.90	0.67	0.73	0.94	0.69	32.08	1.19	0.73	0.97	0.70
Median Filter	29.99	3.77	1.00	0.01	0.01	29.46	4.05	1.00	0.05	0.05	28.89	4.40	1.00	0.10	0.10
Fast Removal	38.82	0.42	0.85	0.09	0.08	29.44	1.41	0.80	0.36	0.29	24.88	3.17	0.72	0.53	0.39
Lee's algorithm	30.02	0.53	0.68	0.38	0.26	29.15	1.01	0.71	0.76	0.54	28.27	1.58	0.71	0.86	0.61
$\mathrm{IND}_{\mathrm{MASK}}$	39.47	0.67	0.67	0.65	0.43	34.56	3.43	0.69	0.91	0.62	31.76	6.44	0.68	0.94	0.64
SD-ROM	29.35	1.29	0.81	0.38	0.31	28.94	4.28	0.83	0.78	0.65	28.18	7.62	0.82	0.87	0.71
None	29.19	0.78	-	-	-	21.84	3.93	-	-	-	19.13	7.41	-	-	-

Table 2. Restoration of the "Boat" image corrupted by 1%, 5% and 10% random-valued impulsive noise.

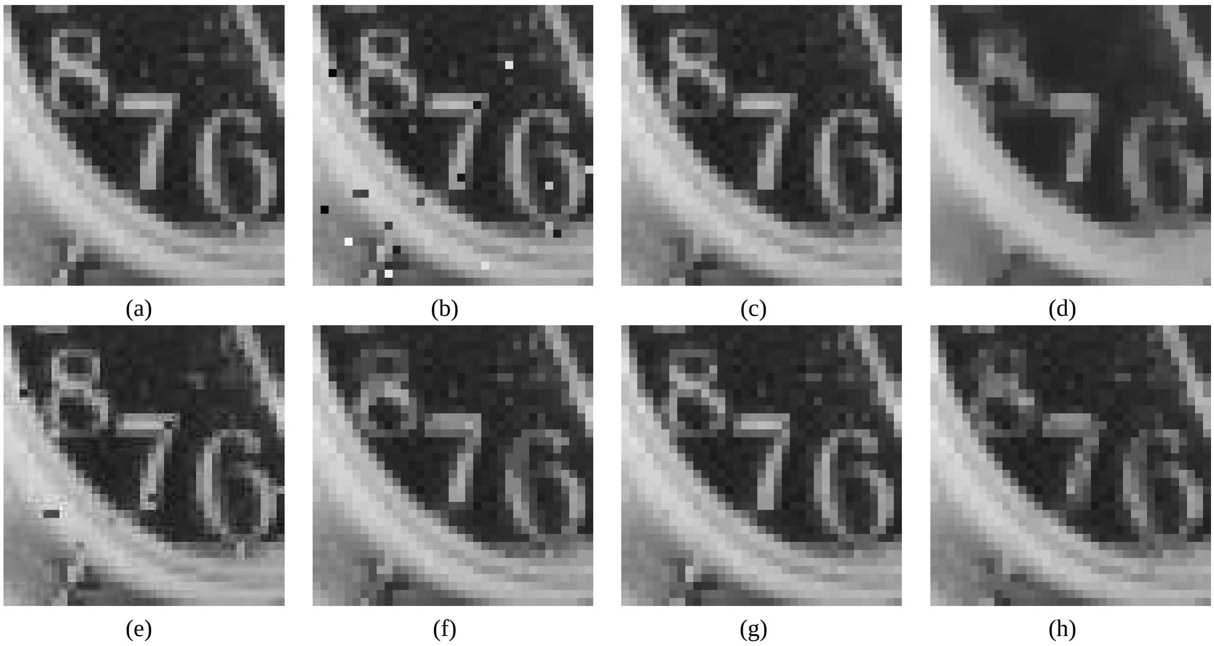

Fig. 3. (a) Cropped part of the original "Clock" image, (b) same area corrupted by 2% random-valued impulsive noise, (c) result of the proposed algorithm, (d) result of 3×3 Median Filter, (e) result of Fast Removal, (f) result of Lee's algorithm, (g) result of $\mathrm{IND}_{\mathrm{MASK}}$, (h) result of SD-ROM.

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