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Efficient Restoration Method for Images Corrupted with Impulse Noise

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Abstract This paper proposes a two-stage adaptive method for restoration of images corrupted with impulse noise. In the first stage, the pixels which are most likely contaminated by noise are detected based on their intensity values. In the second stage, an efficient average filtering algorithm is used to remove those noisy pixels from the image. Only pixels which are determined to be noisy in the first stage are processed in the second stage. The remaining pixels of the first stage are not processed further and are just copied to their corresponding locations in the restored image. The experimental results for the proposed method demonstrate that it is faster and simpler than even median filtering, and it is very efficient for images corrupted with a wide range of impulse noise densities varying from 10% to 90%. Because of its simplicity, high speed, and low computational complexity, the proposed method can be used in real-time digital image applications, e.g., in consumer electronic products such as digital televisions and cameras.

Keywords Average filtering · Impulse noise · Image restoration · Noise reduction · Salt-and-pepper noise

1 Introduction

Images sent electronically from one place to another, via satellite or wireless transmission, or through networked cables, are subject to degradation due to several types of disturbance or noise. Impulse noise, also called salt-and-pepper noise, shot noise, or binary noise, is a common type. Images are often corrupted by impulse noise due to

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errors generated in noisy sensors during image acquisition, faulty memory locations in hardware, or transmission of images in noisy channels [10].

It is important to eliminate noise in the images before subsequent processing, such as edge detection, image segmentation, and object recognition. For this purpose, many filtering algorithms have been proposed in the literature of image processing. Median-based filters have attracted much attention from researchers during the years. However, most median filters are implemented uniformly across the image and thus tend to modify both noisy and noise-free pixels. Consequently, the effective removal of impulse is often accomplished at the expense of blurred and distorted features. To overcome this problem, many algorithms, mainly modified forms of median filters, have been proposed [2–9, 11–19, 21–23]. Different approaches have also been addressed, such as those proposed in [1, 20].

The proposed algorithm in [5] is composed of an efficient impulse detector to determine which pixels are corrupted by fixed-valued impulse noise and an edge-preserving filter to reconstruct the noisy pixels by observing the spatial correlation and preserving the edges efficiently. A two-phase scheme for removing salt-and-pepper noise is proposed in [4]. The pixels which are most likely to be noisy are identified in the first phase. In the second phase of the scheme, a specialized regularization method is used to restore the image. The window size used in this algorithm is large, e.g., 39×39, when the image is highly corrupted by noise. Subsequently, this increases both the computational complexity and the processing time of the algorithm.

The noise adaptive soft-switching median filter proposed in [9] and the selective removal of impulse noise method proposed in [17] are both based on homogeneity information to remove impulse noise. These filters identify possible noisy pixels first and then replace them using the median filter or its variants. Besides the high computational complexity of these methods, the edges and details are not recovered satisfactorily for highly corrupted images.

The proposed algorithm in [15] uses a fuzzy impulse detection technique to detect the locations and values of impulse noise based on a histogram of the noisy image. A filtering step is then used to remove the impulse noise. An improved switching median filter is presented in [23] based on the minimum absolute value of four convolutions obtained using one-dimensional Laplacian operators.

Instead of having no a priori threshold value as in the classical adaptive switching median (ASWM) filter, the threshold value in the ASWM proposed in [3] is computed locally from the intensity values of the image pixels in a sliding window. An algorithm for impulse noise detection is proposed in [8] aiming at providing a solid basis for subsequent filtering. This algorithm consists of two iterations to make the decision as accurate as possible. Two robust and reliable decision criteria are proposed for each iteration.

In [12], restoration of blurred images corrupted by impulse noise or mixed impulse plus Gaussian noise is studied. In this method, a modified total variation minimization scheme is used to regularize the deblurred image and fill in suitable values for noisy image pixels which are detected by median-type filters. An alternating minimization algorithm is employed to solve the proposed total variation minimization problem.

An adaptive two-pass rank order filter to remove impulse noise in highly corrupted images is presented in [22]. An adaptive rank order filter such as the median filter is applied twice in this method. A generalized median-based switching filter, called a multi-state median (MSM) filter is presented in [6]. Using simple threshold logic, the output of the MSM filter is adaptively switched among those of a group of center weighted median (CWM) filters that have different center weights.

A method called boundary discriminative noise detection is proposed in [16] to remove impulse noise from highly corrupted images. A switching median filter incorporated with an impulse noise detector is used to determine the corrupted pixels. A generalization of histogram equalization algorithm is studied in [19]. The *accumulation function* used in this algorithm is used to generate a gray level mapping from the local histogram.

The method proposed in [7] uses a simple threshold operation and a detection mechanism that is estimated based on differences between the outputs of CWM filters with varied center weights and the current pixel of concern. In the first stage of the method in [13], the image pixels are determined to be noisy or not depending on their intensity values. The noise-free pixels are left unchanged, while the noisy pixels are processed in the second stage using median filtering. The size of the median filter used is adaptively changed based on the noise-free pixels in the neighborhood.

A progressive switching median filter is proposed in [21] to restore image contaminated by salt-and-pepper noise. Both the impulse detection and the noise filtering procedures used in the method are progressively applied through several iterations to ensure the removal of noise from the image.

In [11], a directional difference-based switching median filter with robustness that is independent of the noise generation probability is proposed. Since the detector used in this method has the signal estimation capability of the directional difference filter, it can detect impulse noise including that generated at a high generating ratio and as a burst.

In [2], a differential rank impulse detector is proposed based on a comparison of signal samples within a narrow rank window by both rank and absolute value. The alpha-trimmed mean-based method proposed in [14] uses the alpha-trimmed mean in impulse detection in the first stage. In the second stage, the value of each noisy pixel is replaced by a linear combination of its original value and the median of its local window. The decision-based algorithm proposed in [18] replaces the corrupted pixel value by the median of a local window or by its neighboring pixel value according to some proposed decisions.

In [20], an optimal wavelet filter banks method is used instead of a Laplacian smoothing filter for image restoration. In [1], a robust recursive inverse algorithm is proposed to restore images which are mainly corrupted by impulsive noise with low signal-to-noise ratio.

Reviewing these papers shows that an efficient image restoration method that has superior performance in terms of quantitative evaluation and visual quality, low computational complexity, and short processing time is highly desirable.

This paper is outlined as follows. Section 2 describes and analyzes the proposed method. Section 3 presents the experimental results of the proposed method and a comparison with some other state-of-the-art methods. The conclusion is presented in Sect. 4.

2 Proposed Method

In this proposed method, the pixels are divided into two categories: noisy and noise-free pixels, depending on their intensity values. For an image with a dynamic range between 0 and 255, pixels with values equal to 0 or 255, i.e., the minimum and the maximum values, are considered to be corrupted by impulse noise (salt-and-pepper noise) and the remaining pixels are clean [4, 8–10, 21]. The noisy pixels are then processed in the second stage using simple average filtering through an algorithm with low computational complexity. The size of the applied average filter is computed only once, before applying the average filtering, depending on the noise percentage or density. An alternative method for determining the size of the filter is to use a few predetermined values—shown at the end of this section—computed after applying the restoration algorithm on hundreds of noisy images with different noise densities. The size of the average filtering window is adaptively changed in the algorithm depending on how noisy the image being processed is. The proposed method in general uses small window sizes for a wide range of impulse noise densities. Using small window sizes results in processing only neighbors of the corrupted pixel that have higher correlation, and this provides more edge details, leading to better edge preservation. No threshold is needed in the algorithm and no sorting of the values of pixels is needed either since average filtering rather than median filtering is used. This subsequently results in a short run-time processing of the algorithm and its high speed.

2.1 Steps of the Algorithm

The main steps in this two-stage algorithm are as follows.

- Create a "logical" binary matrix that contains the corrupted pixels by impulse noise, i.e., find pixels with intensity values equal to 0 or 255. Accordingly, 1 indicates noisy pixels and 0 indicates noise-free pixels.
- Create a matrix that is the same as the original noisy image except that each corrupted pixel is replaced by zero.
- Find an estimate of the noise density by dividing the total number of the corrupted pixels by the total number of pixels using (1), and then find the size of the average filtering using (2).
- Create a matrix that includes the local sums in each $W \times W$ window of the uncorrupted pixels by summing them up using *convolution*.
- Find the number of uncorrupted pixels in each $W \times W$ window and then compute local averages of uncorrupted pixels.
- Replace corrupted pixels by rounded local averages.

2.2 Size of the Filtering Window

The size of the average filter $W \times W$ used in the method is determined based on the computation of the estimate of the noisy density in the image. The noisy density denoted by D is defined as

$$D = \frac{K}{M.N} \tag{1}$$

where K is the number of pixels which are determined to be noisy in the first stage of the method, and *(M.N)* is the total number of pixels in the image. The size of the filter is computed as follows:

$$W = 2\left\lfloor \sqrt{\frac{2.2}{1-D}} \right\rfloor + 1 \tag{2}$$

where $W = \lfloor T \rfloor$ is the *floor* value of T.

The average filter size can also be roughly estimated based on the noise density, D, computed in (3) shown below.

$$W = \begin{cases} 3 & 0.10 \le D < 0.50 \\ 5 & 0.50 \le D < 0.75 \\ 7 & 0.75 \le D \le 0.90 \end{cases} \tag{3}$$

2.3 Performance Measures

The performance measuring indices of the proposed algorithm are the peak signal-to-noise ratio (PSNR) and the mean absolute error (MAE). For an M by N image with a dynamic range between 0 and 255, i.e., the minimum and maximum pixel values are 0 and 255, respectively, the PSNR (in dB) and MAE are defined by (4) and (5) shown below.

$$\mathrm{PSNR} = 10\log_{10} \frac{(255)^2}{\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(R_{i,j} - X_{i,j})^2} \tag{4}$$

$$\mathrm{MAE} = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left|R_{i,j} - X_{i,j}\right|^2 \tag{5}$$

Here M and N are the total number of pixels in the horizontal and vertical dimensions of the image, and $R_{i,j}$ and $X_{i,j}$ are the pixel values of the restored image and the original image, respectively.

3 Experimental Results

A variety of simulations are carried out to test the performance of the proposed method on several test images as shown below. The size of the filter used in the simulations is computed using (2). The simulations are performed in MATLAB 7.10 (R2010a) on a laptop equipped with a 2-GHz Intel Core 2 Duo CPU and 3 GB RAM.

Table 1 shows the PSNR and MAE of the proposed method applied to the Lena image (512×512 8-bit gray-scale) corrupted by salt-and-pepper noise with a density that varies from 10% to 90% with an increment of 10%. Superior results are clearly shown using small window sizes, W, for that wide range of noise density. The results in Table 1 are shown in Fig. 1. To verify the performance and characteristics of the proposed method, it is also applied to many other images with different noise densities. Table 2 shows the PSNR of the proposed method applied to eight images,

Table 1 PSNR and MAE of the proposed method with different window size $W \times W$ applied on Lena image contaminated with wide range of noise densities

D	W	PSNR (dB)	MAE
10%	3	42.6	0.37
20%	3	39.3	0.75
30%	3	37.0	1.17
40%	3	34.3	1.67
50%	5	31.8	2.64
60%	5	30.8	3.20
70%	5	29.7	3.93
80%	7	27.5	5.40
90%	9	25.4	7.30

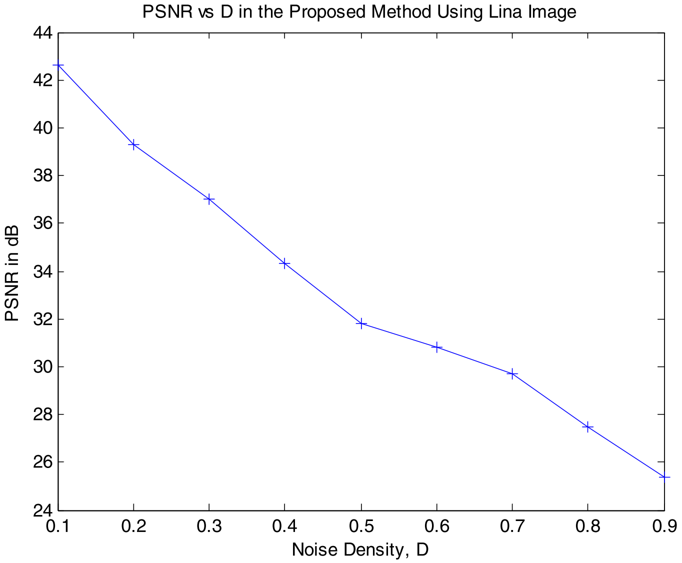

Fig. 1 PSNR vs. noise density, D, in the proposed method using Lena image

including the Lena image, corrupted with low, medium, and high noise densities. The processing time for the Lena image with 10% noise density is 233 msec and that for 90% density is 295 msec. The corresponding processing time for the Bridge image is almost the same. This time is less, and in many times much less, than the processing time in all tested methods among those shown later in Table 3. The processing time increases as the noise density increases since the window size increases. With 10% noise density the window size is 3×3 while for 90% density it is 9×9. Figure 2 shows the first four images in Table 2 before being subjected to noise, after being corrupted by 40% impulse noise density, and the restored image using the proposed method. Figure 3 shows the results for the remaining four images in Table 2 but with impulse noise density equal to 70%. Evidently, fine details of the image are restored,

Table 2 PSNR of the proposed method applied on several images contaminated with three impulse noise densities that represent the entire range of noise levels from low to high

Images	PSNR (dB)		
	$D = 25\%$	$D = 55\%$	$D = 85\%$
Lena	38.1	31.3	26.7
Cameraman	39.1	30.4	25.3
Woman Blonde	30.8	27.6	24.8
Living Room	33.9	27.7	23.9
Woman Dark Hair	44.7	38.0	31.9
Pirate	35.2	29.2	25.1
Eight	34.8	29.9	25.8
Bridge	31.6	26.1	22.5

Table 3 Comparison between PSNR of the proposed method and PSNR of other methods using Lena and Bridge images, each contaminated with 70% impulse noise density

Methods	PSNR (dB)	
	Lena	Bridge
Method [21]	19.5	17.0
Method [6]	19.0	16.4
Method [9]	17.5	15.9
Method [11]	21.8	19.9
Method [23]	23.4	20.1
Method [2]	24.1	22.1
Method [15]	18.4	16.5
Method [14]	19.1	16.9
Method [18]	28.3	23.1
Proposed Method	29.7	24.6

and the visual quality of the proposed method is exceptional. Table 3 demonstrates a comparison of the proposed method with nine more methods using one image with a homogeneous region (Lena image) and another one with high activity (Bridge image), both corrupted by impulse noise with noise density $= 70\%$. The table shows that the proposed algorithm significantly outperforms all other algorithms.

4 Conclusion

In this paper, an efficient, fast, and simple image restoration method based on average filtering is introduced and analyzed. The proposed method is applied on a large number of images contaminated with a wide range of impulse noise densities from low to high levels. Extensive simulation results show a superior performance of the method over many state-of-the-art methods in terms of PSNR, MAE, and runtime. The algorithm uses simple average filtering and a small window size, which results

Fig. 2 Four images before being subjected to noise (*left*), after corruption by 40% impulse noise density (*middle*), and the restored image using the proposed method (*right*)

in its superior speed. Moreover, the method does not require any boundary corrections and does not use any threshold value and still preserves fine details and edges. Because of its simplicity, superior performance, and low computational complexity, the method can be used in real-time digital image applications, e.g., in consumer electronic products.

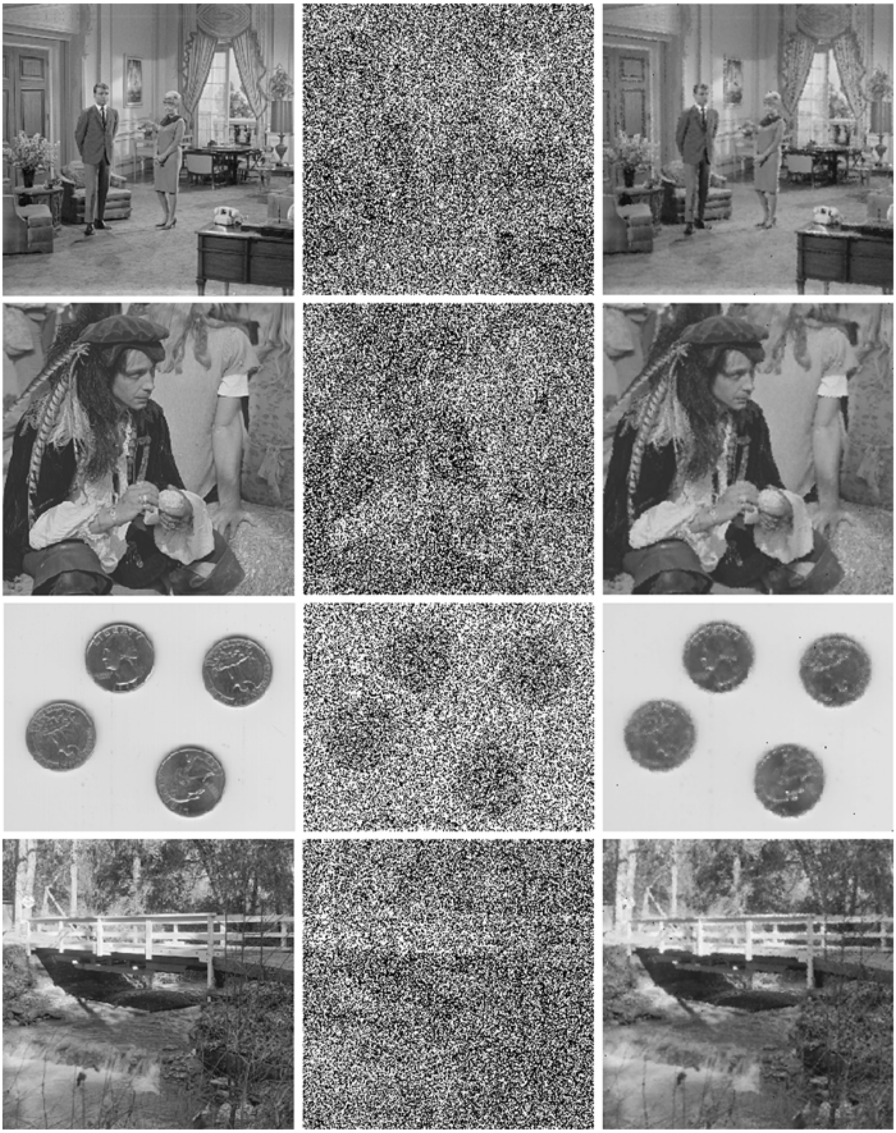

Fig. 3 Four images before being subjected to noise (*left*), after corruption by 70% impulse noise density (*middle*), and the restored image using the proposed method (*right*)

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