An improved adaptive median filtering algorithm for removing salt and pepper noise

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Abstract

Image denoising is the most important part of image processing. It plays a vital role in image processing. An improved adaptive median filter algorithm is proposed in this paper.It mainly remove the salt and pepper noise in the image. The proposed algorithm quickly determines the optimal window size. Then the median pixel is extracted from the effective pixels in the window, and the noise point is effectively reduced with the appropriate value substitution. The window size automatically increases until the appropriate medium value replaces the noise pixel. Compared with all the basic filter, the proposed algorithm reduces the complexity of the algorithm, improve the effectiveness of noise suppression. The image quality has been improved obviously. A lot of simulation of a set of standard grayscale images. The proposed algorithm is more effective in the peak signal-to-noise ratio (PSNR) and other image quality evaluation indexes.

Keywords

Adaptive Median filter; salt and pepper noise; PSNR.

1. Introduction

Digital image processing refers to the process of converting image signal into digital signal and processing it by computer[1]. It mainly involves the modification of digital data and the use of computers to improve the image quality so as to further extract information.. Because of the imaging system, transmission medium and incomplete recording equipment, digital image in the process of formation, transmission and recording, often makes the acquired image by a variety of noise pollution, so in pattern recognition, computer vision, image analysis and video coding, and other fields, in the early period of the noise image processing is extremely important, its treatment effect is good or bad will directly affect the quality and results of follow-up work, is an important part of the early stage of the processing and filtering.

In order to remove impulse noise in digital image, various filtering methods are proposed. Nonlinear filter is an effective method, in which the median filter has a good effect on eliminating impulse noise, and has been widely used.[2]. Median filtering is based on the idea of neighborhood sorting, in which the median value of the pixel in the neighborhood replaces the current pixel. However, when the noise pollution degree is large, the median filtering effect is significantly reduced, and image detail protection and noise elimination become irreconcilable contradictions[3]. In recent years, many scholars have proposed many improvement methods. The standard median (SM) filtering algorithm is simple and fast, but its noise reduction ability is limited, and it is easy to cause image blurring and loss of edge details. Weighted median filter[4].The operation is simple and fast, but its noise reduction ability is limited, which is easy to cause image blurring and loss of edge details[5-7] . The weighted median filter wave can adjust the size of the weight to achieve different degrees of smoothness of the image, but it will change the background and target pixels, resulting in different degrees of image distortion[8-10] .The switching median filter only filters the polluted pixel points, effectively avoiding the image distortion problem mentioned above, but the size of the filter window will seriously affect the filtering quality[11].Fuzzy weighted median filter (FWMF) carries out weighted median filter through fuzzy membership function to achieve filtering, but if the fuzzy function is selected improperly, it is difficult to guarantee the filtering effect. Adaptive median filter (AMF) can adjust the filtering window adaptively according to the noise pollution degree, so as to better protect the image details. Although these algorithms have achieved some filtering effects, they still have many limitations and shortcomings[12-14] .

The maximum and minimum window sizes of traditional adaptive median filter are fixed, which is usually set according to experience, so it is difficult to process images with different noise concentrations. When the window size is large, the traditional adaptive median filter needs a long time to obtain the maximum, minimum and median of the image grayscale in the window. Based on the common adaptive median filtering algorithm, an improved adaptive median filtering algorithm is proposed. The algorithm first determines the optimal window size through the position relationship between the effective pixel and the center pixel of the window, and then only sorts the effective pixel points to take the median value, which not only ensures the reduction of computational complexity of adaptive median filtering, but also ensures the improvement of noise reduction effect.

2. Median Filter

2.1 Standard Median Filter

A simple median filter[11] uses the median of the window to replace the central pixels considered by the window. If the center pixels is (Pepper) or (salt), it will be replaced by the middle value of the window, which will not be or. The major drawback of standard median filter is that even if the pixels under consideration is uncorrected (other than 0 or 255), it is replaced by the median of the window. This will damage the overall visual quality of the image.

In addition, a simple median filter cannot maintain edges. It works as follows:. The window sorted in ascending. Median is the middle value after the sort. Therefore, the undamaged pixels are replaced by the median value of the window.

$$\begin{array}{ccc} \text{Sample window} & & \text{Output} \\ \begin{bmatrix} 46 & 64 & 82 \\ 255 & (45) & 52 \\ 64 & 64 & 82 \end{bmatrix} & \longrightarrow & \begin{bmatrix} 46 & 64 & 82 \\ 255 & (82) & 52 \\ 64 & 64 & 82 \end{bmatrix} \end{array}$$

As shown below, if the considered pixel is destroyed, the impulse noise will be removed in the same way[12].

$$\begin{array}{ccc} \text{Sample window} & & \text{Output} \\ \begin{bmatrix} 46 & 64 & 82 \\ 255 & (255) & 52 \\ 64 & 64 & 82 \end{bmatrix} & \longrightarrow & \begin{bmatrix} 46 & 64 & 82 \\ 255 & (82) & 52 \\ 64 & 64 & 82 \end{bmatrix} \end{array}$$

2.2 Improved Self-adaptive Median Filter

Based on the classical adaptive median filtering algorithm, an improved adaptive median filter (IMF) based on dynamic window size is proposed. It is executed as follows:

(1)The noise pixel $g(x,y)$ are detected by comparing the simple thresholds and averages around the target pixels.

(2)Select the 3×3 window centered at the noise pixels $g(x,y)$. If there exists informative pixels around $g(x,y)$, $g(x,y)$ is replaced by the median value of informative pixels in the window.

(3)If there is not enough information pixels around $g(x,y)$, the window will be expanded to 5×5 (7×7) and repeat the above steps.

Because noisy pixels are replaced by the median values got from informative pixels, the IMF algorithm avoids the spread of noisy signals in the adjacent efficiently during filtering. However, the original pixel distribution is not considered in the recovery process. There is always a significant correlation between adjacent pixel values in natural images.

There are often significant correlations between adjacent pixel values in a nature image. Therefore, noise pixels replaced by adjacent values outside the median value are sometimes more accurate.

3. Proposed approaches

3.1 Determine the distance of effective pixels

When we analyze the local pixel value distribution, it can be found that a pixel value is often equal or similar to its adjacent pixel values in original digital images.

Table.1 shows the coordinate definition for a window, and Table.2 gives the local pixel value distribution of small image blocks in Lena image

Table.1 A filtering window of size 3×3

g(x-1,y-1)	g(x-1,y)	g(x-1,y+1)
g(x,y-1)	g(x,y)	g(x,y+1)
g(x+1,y-1)	g(x,y+1)	g(x+1,y+1)

Table.2 Local pixel distribution for a small region

148	148	148	147
148	148	149	147
148	149	149	147

When focusing on the image block, we find that the values of the adjacent pixel values along the columns, columns or diagonal lines in the local region show certain regularity. We call it a priori knowledge. Furthermore, the following rules are defined for the direction of movement of windows.

If the coordinate distance $\mathrm{r} = |i-m|$ from I to Y causes the window size to be wrong, the result will be EFCH.

So that Y can't be filtered in the window. Therefore, we should compare the difference between the horizontal and vertical lengths, take a larger $|\mathrm{j}-n|$ and make $\mathrm{r} = |\mathrm{j}-n|$, $Y \in MINO$. Similarly, for H point $r = |i-z|$, this improvement reduces the number of times.

3.2 Noise detection by Extreme value distribution

In order to identify impulse noise, we first define the same matrix as the dimension of the image to be detected[13-18]. A Matrix B is a digital noise image that needs to be detected (where g represents the location of each point). Let's say, matrix $\left[a_{ij}\right]$ is a digital noise image that needs to be detected (where i, j represents the location of each point). T_Z Represents a filter window with a size of $(2n+1)\times(2n+1)$ (where n is a positive integer).

T_U Represents a noise detection window. $T\left[a_{ij}\right]$ Indicates that a point a_{ij} is centered as a window.

(1)Through noise detection, we can generate a binary symbol image matrix $\left[K_{ij}\right]$ which represents the noise distribution in the original image.

If $K_{ij}=1$ is used in the logo image matrix, the pixel of the original image is impulse noise. On the contrary, if in the logo image matrix $K_{ij}=0$, the point a_{ij} is the original image pixel.

In the process of noise detection is initialized to all 0 matrices. According to the result impulse noise detection, the element value in the matrix is set to 1 or the original value is 0.

(2)For sorting $N=(2n+1)\times(2n+1)$ points in the noise detection window based on point a_{ij}, we get a vector $B_{ij}=\left[a_{ij1},a_{ij2},a_{ij3},\ldots,a_{ijN}\right]$.

Where $a_{ij1}<a_{ij2}<\ldots<a_{ijN}$. When the sorted point a_{ij} is near the endpoint of vector D_{ij}, point a_{ij} can be a noise point. Finally, the first condition of the noise detection shown in the expression of satisfaction (3.1) may be the noise point:

$$\begin{cases} G\left(a_{ij}\right)\le m \\ G\left(a_{ij}\right)>N-m+1 \end{cases} \tag{3.1}$$

In the formula (3.1), function $G(a_{ij})$ returns the order value of point a_{ij} in the sorted vector D_{ij}. Obviously, there is always a m value that can contain all the noise points in the noise image. On the contrary, however, it is not true. Because of the sorted signal points (which are not contaminated by noise in the image), especially the edge details in the image may also fall near the two ends of the vector D_{ij}. Especially when the PSNR is very high, the false detection rate will be very large.

In order to detect noise points better, we can further examine the specific gray values of point a_{ij}. When the gray value of a point a_{ij} exceeds the range of a parameter T, it may be a noise point. The second conditions of noise detection are as follows:

$$a_{ij}\in\left[0,T\right]or\left[255\text{-}T,255\right] \tag{3.2}$$

The experimental results show that the gray value of noise-contaminated pixels will change within the range of $\left[0,10\right]$ and $\left[245,245\right]$.

If a certain point in the image satisfies both the formula (3.1) and the formula (3.6) at the same time, we can consider it to be a noise point. In this way, the corresponding symbol in the logo image matrix can be 1. Conversely, it is considered a signal point, and the corresponding position in the logo image matrix is labeled as 0. In this way, two input images $\left[k_{ij}\right]$ that reflect the noise distribution can be obtained.

$$k_{ij}=\begin{cases}1, \\ 0, & other\end{cases} \tag{3.3}$$

3.3 Filtering Implementation

After detecting the noise pixels, the proposed method focuses on filtering noisy pixels at the boundaries of the image[16]. If a sample (pixel of the image) is noise, it is replaced by the value calculated from other samples in the observation window.

Since there may be more than one pulse in the filter window, the gray value of the noise point should be reconstructed with the nonlinear idea. The method of filtering noise is based on the idea of standard median filtering algorithms. When filtering, first select the select the filter window T_z. In the noise mark matrix $\lfloor k_{ij} \rfloor$. For a point, if the point is $k_{ij} = 1$, it means that the point is a noise point. We need to deal with it in two cases.

If there is a signal point in the neighborhood ($n > 0$, n represents the number of signal points), we calculate the median value of the point center filter window.

$$z_{ij} = \begin{cases} med\left(k(i,j)\right), n \in odd \\ (\mathrm{k}_{med1}(i,j) + k_{med2}(i,j))/2, \quad n \in even \end{cases} \tag{3.4}$$

Among them, n is the number of points marked 0 , and k_{ij} is the gray value of points marked 0, represents the gray value of the two points in the middle after sorting.

If there are no image points around the noise points, the points

should not be processed. It is directly assigned to the point b_{ij} of the corresponding position of outp ut matrix $\left[b_{ij}\right]$.

The noise filtering process can be described as: The filter is first performed with the length of the 3×3 window. The specific operation formula (3.5) shows that:

$$b_{ij} = \begin{cases} v_{ij}, k_{ij} = 1, n > 0 \\ a_{ij}, \quad else \end{cases} \tag{3.5}$$

When the noise point a_{ij} i

s modified by median filtering, it can be

regarded as the image point. We need to change the mark from 1 to 0 in

the binary sign matrix $\left[k_{ij}\right]$ reflecting the noise distribution.

$$k_{ij} = \begin{cases} 0, b_{ij} = v_{ij} \\ 0, \end{cases} \tag{3.6}$$

When $\left[b_{ij}\right]$ is obtained, we examine whether there is a mark in the binary symbol matrix $\left[k_{ij}\right]$. If it exists, the image $\left[b_{ij}\right]$ is used as the original input image $\left[a_{ij}\right] = \left[b_{ij}\right]$. Expand the filter window to 5×5 and repeat the above steps to get $\left[k_{ij}\right]$. When there is no point marked in the binary identity matrix $\left[b_{ij}\right]$, the loop is stopped. Finally, the image $\left[b_{ij}\right]$ is output as the filtering result of the whole algorithm.

4. Significance measures

4.1 PSNR

We have tested our proposed algorithm for different levels of noise ranging from as low as to as high as .

The experimental results have been gauged using the mean square error (MSE)[19]and peak signal-to-noise ratio (PSNR) measures that have been given below[20].

$$MSE = \frac{1}{mn}\sum_{x=0}^{m-1}\sum_{y=0}^{n-1}\left(A(x,y)-R(x,y)\right)^2 \tag{4.1}$$

Where A and R are the original and the restored images having are resolution of $m \times n$.

$$PSNR = 10\log_{10}\left(\frac{\max^2}{MSE}\right) \tag{4.2}$$

Where max is the maximum possible pixel value of the image and its value is in the case of a gray scale image.

4.2 SSIM

The SSIM index[21] is a full reference metric, in other words,the measuring of image quality based on an initial uncompressed or distortion free image as reference. SSIM is designed to improve on traditional methods like peak signal to-noise ratio and mean-squared error, which have proved to be inconsistent with human eye perception. SSIM is a new paradigm for quality assessment, based on the hypothesis that the HVS is highly adapted for extracting structural information. The measure of structural similarity compares local patterns of pixel intensities that have been normalized for luminance and contrast. In practice, a single overall index is sufficient enough to evaluate the overall image quality. Hence, a mean SSIM (MSSIM) index is used as the quality measurement metric.

$$SSIM = \frac{\left(2\mu_x\mu_y + C_1\right)\left(2\sigma_{xy} + C_1\right)}{\left(\mu_x^2 + \mu_y^2 + C_1\right)\left(\sigma_x^2 + \sigma_y^2 + C_1\right)} \tag{4.3}$$

$$MSSIM = \frac{1}{M}\sum_{m=1}^{M} SSIM\left(x_m, y_m\right) \tag{4.4}$$

5. Results and Discussion

To prove the advantages of the proposed method, we compare its performance of revising the pepper and salt noise polluted image with several classical median filters which are standard median filter(SMF)[22], Improved Standard Median filter(ISM) [23]and Improved median filter (IMF)[24]. The comparison results got from 512×512, 8 -bits/pixel gray-level Lena image and 512×512, 8 -bits/pixel gray-level retina images with different noise densities(ND) of pepper and salt noise are shown in Fig.2 and Fig.3.

The proposed method is better than the IMF[24] to deal with the edges and details. The performance of different methods is summarized in Fig.4 and Fig.5. Experimental results show that IMF and the proposed method have better performance in filtering the pepper and salt noise than other filters. However, when the noise density increases, the performance of ISM degrades. However, when the noise density is greater than 0.7, the performance of the proposed method is better than IMF to deal with the edges and details.

In Fig.4, the restoration results have been shown for the noise density 0.3 for corrupted Retina image. Among all these filters, the proposed method gives the best performance in terms of noise suppression and detail preservation.

Using TMF and ISM we are able to remove some amount of noise but a large amount of noisy pixels are present in the output image when noise density is high. Also in IMF some unwanted gray values occur after filtering.

In Fig.2, the restoration results have been shown for the noise density 0.7 for corrupted Lena image.

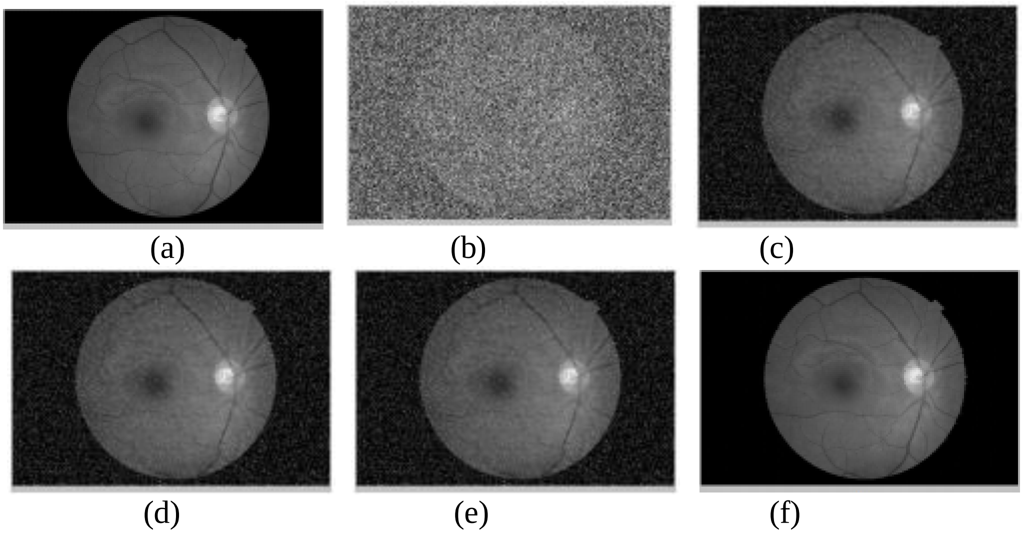

Fig.2 Reconstructed images using the proposed scheme and different denoising schemes for corrupted Lena image: (a) original noise-free image, (b) 30% noise corrupted, (c) TMF, (d) ISM, (f) proposed scheme.

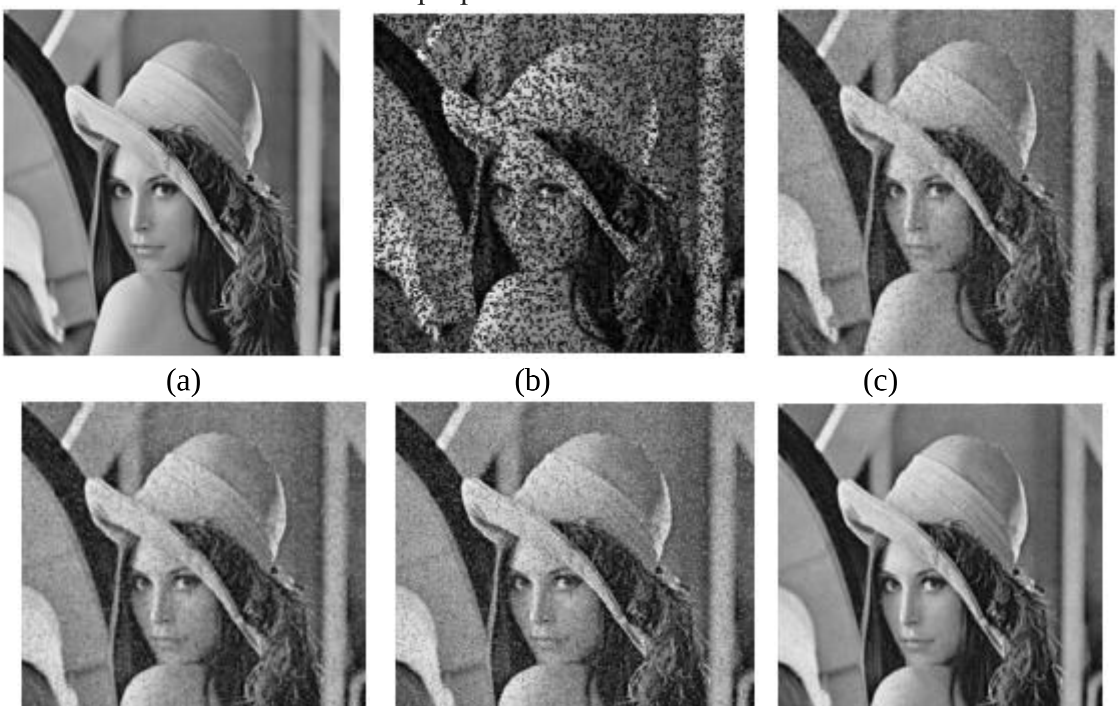

Fig.3 Reconstructed images using the proposed scheme and different denoising schemes for corrupted Lena image: (a) original noise-free image, (b) 70% noise corrupted, (c) TMF, (d) ISM, (e) IMF,(f) proposed scheme.

The proposed method is also compared with other methods in terms of PSNR for high noise levels as shown in table 4. The result shows that the proposed filter performed better than ISM.

It is seen from Tab. 3 that the performance of the proposed method is better than other algorithms at different noise densities from 10% to 90%.Based on SMF, ISM introduced noise detection to discriminate uncorrected pixels from the corrupted pixels. Only the corrupted pixels are filtered. Thus, it provides higher PSNR and lower MSE than IMF.

Tab.3 The PSNR values of different denoising methods for Lena image at different noise densities.

Method	Noise density										
	10	20	30	40	50	60	70	75	80	85	90
SMF	30.2	29.43	28.26	27.2	25.18	23.4	20.5	18.07	16.17	14.8	12.95
ISM	31.2	30.52	29.58	28.46	26.85	24.15	21.2	19.31	17.57	15.93	14.3
IMF	32.96	31.03	30.25	29.73	28.94	27.83	26.59	25.96	25.05	24.31	23.74
Proposed method	33.05	32.53	31.54	30.79	29.75	29.02	28.38	27.83	27.03	26.85	26.39

Tab.4 The MSE values of different denoising methods for Lena image at different noise densities.

Method	Noise density										
	10	20	30	40	50	60	70	75	80	85	90
SMF	9.59	11.2	12.73	13.97	16.49	21.75	29.84	37.93	45.84	56.82	68.4
ISM	8.61	9.79	11.07	12.73	15.95	19.74	27.38	33.54	41.3	49.73	58.72
IMF	8.2	9.03	10.16	11.94	12.14	13.2	14.95	15.83	17.3	18.87	20.31
Proposed method	7.53	8.34	8.85	9.5	10.41	11.38	12.27	12.75	14.35	14.69	15.32

The proposed method is also compared with other methods in terms of PSNR for high noise levels as shown in table 4. The result shows that the proposed filter performed better than TMF and ISM.

To demonstrate the performance of the proposed filter, a Lena image with a noise density of 0.7 is adopted. As shown in Table 3, the value of MSE is low, PSNR is high, and SSIM is also very high, which indicates that the performance of the proposed filter is better than that of other filters. In addition, IMF can change the window size of different noise densities to collect enough information pixels to provide better performance.

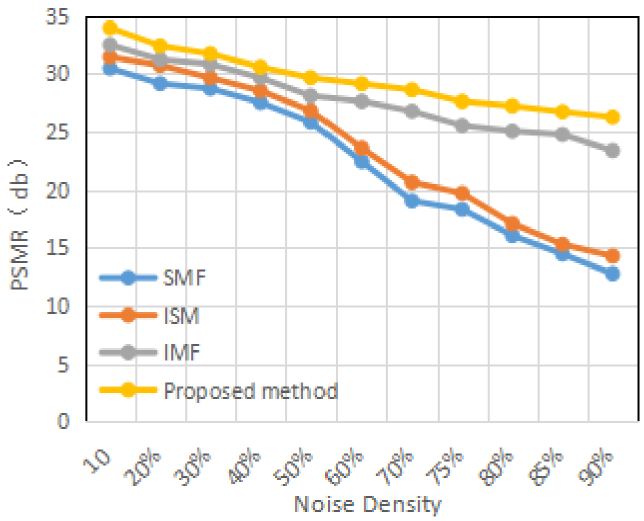

Fig.4 Comparison graph of PSNR at different Noise densities for Lena image

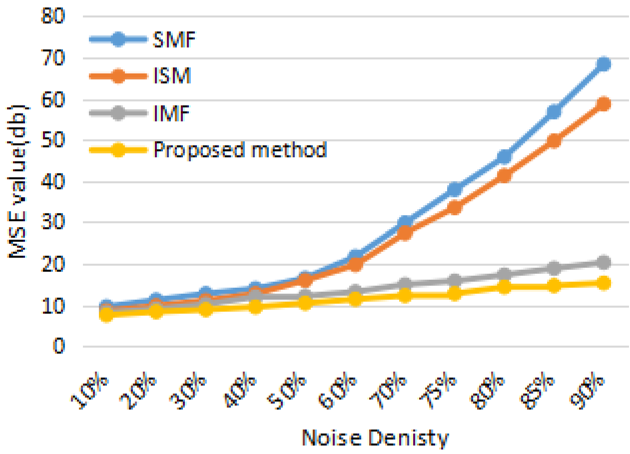

Fig.5 Comparison graph of MSE at different Noise densities for Lena image

Finally, considering the feature of local pixel distribution in the original image, the proposed method extracts noise pixels from the local pixel value, and makes full use of the filtering feature and the correlation between adjacent pixels. Therefore, the experimental results show that the proposed method has the best filtering performance in the four test methods. Figures 4 and 5 shows that the proposed method has better performance and smaller error.

6. Conclusion

A self-adaptive median filter based on local pixel distribution information to remove pepper and salt noise is presented in this paper. The proposed method can not only achieve better image quality, but also have shorter computation time. And our method is simple and easy to be understood. Simulation results reveal that the proposed method provides better performance than the existing method presented for the corrupted by highly noise density in terms of noise suppression and detail preservation. The proposed method gives an efficient filter frame-work, and is suitable for real-time implementation.

Experimental results show that the performance of the proposed method is much superior to that of classical median filter. It performs better than that of the traditional filtering techniques and we hope that our effort will help to improve the future experiments over image processing and performance analysis. In future we will try to explore the effect of other filtering techniques over noisy image and upgrade them according to achieve the better performance.

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