

# Restoration of Images Contaminated by Mixed Gaussian and Impulse Noise using a Complex Method

Gao Yinyu, Nam-Ho Kim, *Member, KIMICS*

**Abstract**— Many approaches to image restoration are aimed at removing either gauss or impulse noise. This is because both types of degradation processes are distinct in nature, and hence they are easier to manage when considered separately. Nevertheless, it is possible to find them operating on the same image, which produces a hard damage. This happens when an image, already contaminated by Gaussian noise in the image acquisition procedure, undergoes impulsive corruption during its digital transmission. Here we proposed an algorithm first judge the type of the noise according to the difference values of pixel's neighborhood region and impulse noise's characteristic. Then removes the gauss noise by modified weighted mean filter and removes the impulse noise by modified nonlinear filter. The result of computer simulation on test images indicates that the proposed method is superior to traditional filtering algorithms. The proposed method can not only remove mixed noise effectively, but also preserve image details.

**Index Terms**— Image restoration, mixed noise, image details.

## I. INTRODUCTION

GENERALLY noise can interpreted as “Unwanted signals”. Over several decades, noise sources causing for digital image degradation has been modeled as the additive Gaussian white noise (AWGN), impulse noise, mixed Gaussian and impulse noise, etc. Impulse noise is characterized by replacing original image's pixel values with extremely high or low values. AWGN is characterized by adding to each image pixel a value from a zero-mean Gaussian distribution during image acquisition. Mixed noise is characterized by first adding the AWGN to the image and then replacing a portion of pixels with random value. It could occur in a case when an image suffers from both sensor faults and transmission noise. The mixed model can be regarded as a more general and challenging noise model than a pure AWGN model or a pure impulse noise model.

Traditionally, there are two kinds of method to remove mixed noise. One is linear filter, such as mean filter (MF). This filter can effectually remove gauss noise, but it ineffective in removing impulse noise, so this method not good enough to remove mixed noise. The other is nonlinear filter, such as, standard median (SM) filter, center weighted median (CWM) filter, Min-max filter. These filters can remove impulse noise effectively, but they are ineffective to gauss noise. Using the linear filter or the nonlinear filter singly cannot remove the mixed noise.

In this paper, to remove mixed noise and preserve image details, we proposed an algorithm that first judges the type of the noise according to the difference values of pixel's neighborhood region and impulse noise's characteristic. Then removes mixed noise by complex method that the gauss noise is processed by modified weighted mean filter and the impulse noise filtered by modified nonlinear filter. We employ the peak signal to noise ratio (PSNR) to illustrate the quantitative quality of the reconstructed image for various methods.

## II. CONVENTIONAL ALGORITHM

### 2.1. Standard median filter

SM filter is widely used for impulse noise elimination due to good smoothing performance for impulse noise 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).

$$W = \{(s, t) | -N \leq s \leq N, -N \leq t \leq N\} \quad (1)$$

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.

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

Where,  $X(i, j)$  is denoted as input value,  $Y(i, j)$  is the output value and  $\text{med}\{\cdot\}$  is denoted as median value. The SM filter can remove the impulse noise effectively, but it can't remove gauss noise very well, so it works not good enough to remove mixed noise. And SM filter can't

Manuscript received April 13, 2011; revised June 7, 2011; accepted June 13, 2011.

Gao Yinyu is with the Department of Control & Instrumentation Eng., Pukyong National University, Busan, 608-737, Korea (Email: bestgaoyinyu@gmail.com)

Nam-Ho Kim (Corresponding Author) is with the Department of Control & Instrumentation Eng., Pukyong National University, Busan, 608-737, Korea (Email: nhk@pknu.ac.kr)

preserve image details.

### 2.2. Center weighted median filter

WM filter is defined as equation (3).

$$Y(i, j) = \text{med}\{M(s, t) \forall X(i + s, j + t) \mid (s, t) \in W\} \quad (3)$$

Here,  $M(s, t)$  is the weight which for the pixels at the position of  $(s, t)$  and  $\forall$  means for copying. In obtaining the output  $Y(i, j)$ , the WM filter generates  $M(s, t)$  copies of  $X(i + s, j + t)$  for each  $(s, t) \in W$ . The output after filtering by WM filter is the median value of the pixels.

The special situation to WM filter is the CWM filter, which gives more weight to the center value and the other pixels in the window are given weight for 1, in the other word,  $M(s, t) = 1$  [3]. The output  $Y(i, j)$  of the CWM filter is given by

$$Y(i, j) = \text{med}\{X(i + s, j + t), 2K \forall X(i, j) \mid (s, t) \in W\} \quad (4)$$

Though the CWM filter performs better than SM filter on preserving details, it also can't remove the mixed noise very well.

### 2.3. 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  $(i, j)$  [4]. MF is the most basic linear type and it is denoted as (5).

$$Y(i, j) = \frac{1}{Z \times Z} \sum_{i, j} X(i + s, j + t) \quad (5)$$

$Z \in W, \quad Z = 2N + 1$

## III. PROPOSED METHOD

### 3.1. Noise Estimation

The estimation of noise point 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 noise points gray are discontinuous in most directions. It means if a pixel is edge pixel, it has the maximum difference value between this pixel and neighborhood region pixels in one or several directions [5]. If a pixel is impulse noise point, where the impulse noise

pixels can only have extreme values, it has the value of 0 or 255. If the pixel doesn't satisfy these conditions, then we treat it is noise-free pixel that the original value will be the resorted image's pixel.

The size of the filter window is  $3 \times 3$ .  $X(i, j)$  is the center pixel of the filter window.  $d_i$  is the difference between the center pixel and eight neighborhood region pixels. Set a threshold  $T_1$ . Judge the type of the noise according to the number of pixel point ( $N_d$ ) which satisfy  $d_i > T_1$ . Here,  $N_d$  is the number of detail points in neighborhood region.

The selection of threshold  $T_1$  is related to the image detail characteristics and it independent in the degree of noise pollution. The threshold should be large if the image has abundant detail information. Otherwise, if the image has a lot of smooth region, the threshold should be valued smaller appropriately. If the value of  $T_1$  is smaller, the image can be made clearer in details, but the ability will recede in restraining gauss noise. So the appropriate value of  $T_1$  is determined by experiment.

### 3.2. Noise Suppression Method

Because of the conventional algorithms can't preserve image details, which causes image blur. In order to preserve details, this paper proposes the method that uses complex algorithms.

#### A. Impulse Noise Suppression

If the center pixel is valued 0 or 255, it is impulse noise. Then propose a modified nonlinear filter that well performance at removing impulse noise and preserve details. This algorithm consists of two stages: noise detection and noise removal. The noise detection aims at identifying the pixels corrupted by the impulse noise. In this method identifies impulse noise values is the 255 or 0.

Step 1. If the noise detection is noise, filter the image use proposed filter, else no filtering, keep the noise free pixel.

Step 2. Under the sub window exist noise free pixel, and then calculate the mean value of noise free pixels. Else if all the pixels identified as noise in the sub window, then calculate the mean value of all the pixels in the window. The mean value denoted as (6). Where,  $M_s$  is the mean value.

$$M_s = \begin{cases} \frac{S_{no}}{N_n} & \text{if}(N_n \neq 0) \\ \frac{S_{all}}{(2N + 1) \times (2N + 1)} & \text{if}(N_n = 0) \end{cases} \quad (6)$$

Here,  $S_{no}$  is sum of the noise free pixels which ignoring the maximum (255) or minimum (0) in the mask, and  $N_n$  is the total number of noise free pixels in the mask.  $S_{all}$  is the sum of all pixels under the sub mask,  $(2N + 1) \times (2N + 1)$  stands for mask size.

Step 3. If there is noise free pixel in the sub mask, continue to calculate the valance between mean value and noise free pixel.

$$\Delta P_{m-} = \min\{|P - M_s|\} \quad \text{if}(P - M_s) < 0 \quad (7)$$

$$\Delta P_{m+} = \min\{|P - M_s|\} \quad \text{if}(P - M_s) > 0 \quad (8)$$

Here,  $P$  is each noise free pixel,  $\Delta P_{m-}$  is the absolute value when the valance is less than 0 between  $M_s$  with  $P$ .  $\Delta P_{m+}$  is the opposite situation that the valance is greater than 0 between  $M_s$  with  $P$ .

$$Y(i, j) = \begin{cases} \frac{(M_s - \Delta P_{m-}) + M_s}{2} & \text{if}(\Delta P_{m-} < \Delta P_{m+}) \\ \frac{(M_s + \Delta P_{m+}) + M_s}{2} & \text{if}(\Delta P_{m-} > \Delta P_{m+}) \\ M_s & \text{if}(\Delta P_{m-} = \Delta P_{m+}) \end{cases} \quad (9)$$

Where,  $Y(i, j)$  is the output after filtering. If the value of  $\Delta P_{m-}$  and  $\Delta P_{m+}$  is different, then, the output image filtered as (9), else if the value of  $\Delta P_{m-}$  and  $\Delta P_{m+}$  take same value, then the value  $M_s$  which calculate as (6) will be the output.

If there is no noise free pixel in the sub mask, the mean of all the pixels will be the output, this situation will happen when impulse noise's density is very high.

### B. Gaussian Noise Suppression

If  $N_d = 0$ , the center pixel point is gauss noise point. Remove this noise by using following modified weighted mean filter. The weighted values change base on standard deviation ( $\sigma_m$ ) for mask. Fig. 1 shows the filtering mask in this paper. From the Fig. 1, we can see that the pixels which near to the center pixel are given the weight values are  $m_{k2}$ , and the pixel at diagonal, the weighted value is  $m_{k1}$ .  $m_{k3}$  is the weight gives to the center pixel. The weight values must follow next condition.

$$m_{k3} > m_{k2} > m_{k1} \quad (10)$$

Here,  $k = 1, 2, 3$  and  $k$  stands for the level of  $\sigma_m$  include in.

Because center pixel effect more than others region's pixel to the result so in this paper gave the large value to it, and. And the pixels near to the center pixel also play a important role to output value, so gave the second large value to the weight  $m_{k2}$ .

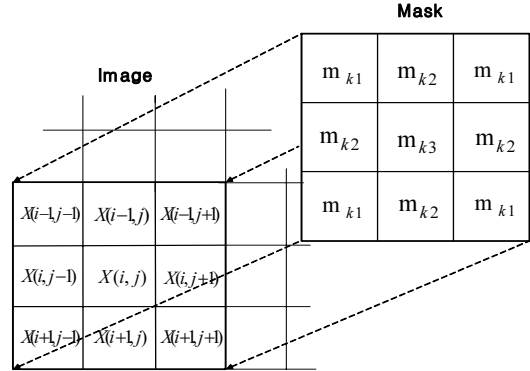


Fig. 1. Filtering mask.

Standard deviation of sub window is compared with threshold  $t_1$  and  $t_2$ . So in this paper according to the result of comparing be separated to three levels. Here,  $t_1 > t_2$ . The value of threshold  $t_1$  and  $t_2$  are selected on the basis of experimentation. The appropriate value of  $t_1$  is 14~20 and  $t_2$  is 6~12. So there are three levels of standard deviation and the weighted values are described as follows:

1, If  $\sigma_m > t_1$ , the weighted values will be calculated as formula (11).

$$\begin{cases} m_{11} = \frac{t_1 + t_2 - 3}{t_1^2 t_2 - t_1 t_2^2 - 3t_1 t_2 - 3t_2^2} \\ m_{12} = \frac{2(t_1 + t_2 - 3)}{t_1^2 t_2 - t_1 t_2^2 - 3t_1 t_2 - 3t_2^2} \\ m_{13} = 1 - m_{11} - m_{12} \end{cases} \quad (11)$$

2, If  $t_2 < \sigma_m \leq t_1$ , the weighted values to the different regions are described as (12).

$$\begin{cases} m_{21} = \frac{t_1 - t_2 + 2}{t_1^2 - t_2^2 - 3t_1 - 3t_2} \\ m_{22} = \frac{2(t_1 - t_2 + 2)}{t_1^2 - t_2^2 - 3t_1 - 3t_2} \\ m_{23} = 1 - m_{21} - m_{22} \end{cases} \quad (12)$$

3, If  $\sigma_m \leq t_2$ , we can calculate weighted values as formula (13).

$$\begin{cases} m_{31} = \frac{t_2 + 1}{t_2 t_1 - t_2} \\ m_{32} = \frac{t_2 + 10}{t_2 t_1 - t_2} \\ m_{33} = 1 - m_{31} - m_{32} \end{cases} \quad (13)$$

The output after filtering is:

$$Y(i, j) = \sum_{s=-1}^1 \sum_{t=-1}^1 X(i+s, j+t) \times m_{kl} \quad (14)$$

$k = 1, 2, 3; \quad l = 1, 2, 3$

#### IV. SIMULATION RESULT

To verify the performance of the proposed method in this paper, the algorithm in this paper is compared with the SM filter, CWM filter and MF. The proposed method is tested using  $512 \times 512$  standard image Lena, the image is corrupted complexly by impulse noise with density of 30% and AWGN with the standard deviation 10 for the simulation. In addition to the visual quality, the performance of the proposed method and other standard algorithms are quantitatively measured by the following parameters such as peak signal to noise ratio (PSNR), mean square error (MSE).

Mean Square Error (MSE):

$$\text{MSE} = \frac{\sum_{i,j} O(i, j) - Y(i, j)}{R \times C} \quad (15)$$

Peak Signal to Noise ratio (PSNR):

$$\text{PSNR} = 10 \lg \left( \frac{255^2}{\text{MSE}} \right) \quad (16)$$

Where  $R$  and  $C$  are the total number of pixels in the horizontal and vertical dimensions of the images,  $O(i, j)$  is the pixel value of original image,  $Y(i, j)$  is filtered image pixels, respectively.

Fig. 2 shows the simulation result of the Lena ( $512 \times 512$ ) image which corrupted by mixed noise is restored by conventional algorithms and proposed method. In the Fig. 2, (a) is the original image; (b) is the noisy image that corrupted by impulse noise with the density of  $p=30\%$  and AWGN with the standard deviation of  $\sigma = 10$ . (c)~(f) show the restoration results of Lena image by SM ( $3 \times 3$ ) filter, CWM ( $3 \times 3, C=3$ ) filter, MF ( $3 \times 3$ ) and the proposed filter respectively.

Visual comparisons among these filtered images show that the classical methods give a better performance in suppressing impulse noise, especially SM filter and CWM filter. And MF has good capability in gauss noise suppression.



Fig. 2. Simulation results.  
(a) Test image (b) Noisy image (c) SM ( $3 \times 3$ )  
(d) CWM ( $3 \times 3, C=3$ ) (e) MF ( $3 \times 3$ ) (f) Proposed filter

But these conventional algorithms tend to blur the fine details make the image detail lost so much. On the other hand the proposed method has the best filtering effect compared with the traditional filter algorithm. The proposed filter combines the good ability to get rid of mixed noise and rather good ability to protect the detail information.

Fig. 3 compares the noise removal results by changing the impulse noise density with 5% to 70% while fixing the standard deviation of AWGN with 10. From Fig. 3, the proposed filter performs well either the noise density is low or high, so the method has high quality to restore image.

Fig. 4 is to compare the noise removal results by changing the AWGN standard deviation with 5 to 25 while fixing the impulse noise density with 30%. The figure demonstrates that the proposed method separated and removed noise component from complex corrupted

image and shows better PSNR performance than other methods in any noisy standard deviation.

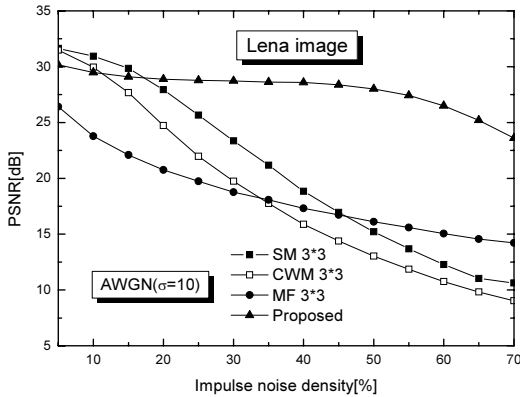


Fig. 3. PSNR with variation of Impulse Noise.

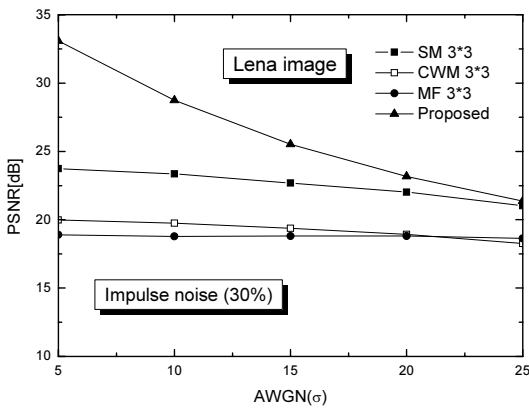


Fig. 4. PSNR with variation of AWGN standard deviation.

Table 1 listed the numerical results in terms of the PSNR for image quality assessment of Lena image.

TABLE 1. PERFORMANCE COMPARISON FOR RESTORING LENA[DB].

$\sigma = 10$	Method			
p (%)	SM (3×3)	CWM (3×3)	MF (3×3)	Proposed
10	30.95	29.97	23.79	29.48
20	27.94	24.73	20.77	28.89
30	23.36	19.74	18.77	28.74
40	18.85	15.89	17.33	28.59
50	15.22	13.04	16.12	28.01

V. CONCLUSIONS

In this paper, a new algorithm is proposed to remove mixed noise in the images. The proposed method first classifies the noise. And then removes the different kinds

of the noise by complex filter. Through the computer simulation on test image, it indicates that the proposed method is superior to traditional algorithms and has good capability in mixed noise suppression, and can reserve image details. And this method is relatively a fast method and suitable to be implemented for consumer electronic products, such as digital camera.

REFERENCES

- [1] Liu Ying-hui, Gao Kun and Ni Guo-qiang, "An Improved Trilateral filter for Gaussian and Impulse Noise Removal," *IEEE 2<sup>nd</sup> International Conference on Industrial Mechatronics and Automation*. pp. 385-388. 2010.
- [2] Ezequiel lopez-Rubio, "Restoration of images corrupted by Gaussian and uniform impulsive noise," *Pattern Recogniton*, vol. 43, pp. 1835-1846, 2010.
- [3] V. R Vijaykumar, P. T. Vanathi, P. Kanagasabapathy and B. Senthilkumar, "A New Efficient Algorithm to Remove High Density Gaussian Noise with Edge Preservation," *IEEE International Conference on Signal Processing, Communications and Networking, Madras Institute of Technology, Anna University, Chennai India*, Jan 4-6, pp. 238-243, 2008.
- [4] M. Juneja and P. S. Sandhu, "Design and Development of an Improved Adaptive Median Filtering Method for Impulse Noise Detection," *IEEE International journal of Computer and Electrical Engineering*, vol. 1, pp. 627-630. Dec. 2009.
- [5] Jiahui Wang and Jingxing Hong, "A New Selt-Adaptive Weighted Filter for Removing Noise in Infrared," *IEEE Information Engineering and Computer Science, ICIECS 2009, International Conference*, pp.1-4. Dec. 2009.



Gao Yinyu

She received the B.S. degree in Electronic Science and Technology engineering from Harbin Engineering University(HEU), China in 2010. She is currently pursuing the M.S. degree in control and instrumentation engineering, Pukyong National University(PKNU), Busan, Korea, Under the supervision of Prof. N. H. Kim. Her research interests include image processing, digital communication and signal processing.



Nam-Ho Kim

Corresponding Author

He received the B.S., M.S., and Ph.D degrees in electronics engineering from Yeungnam University, Korea in 1984,1986 and 1991, respectively. Since 1992, he has been with Pukong National University(PKNU), Korea, where he is currently a professor in the Dept. of Control and Instrumentation Eng. From 2004 to 2006, he was Vice Dean of the College of Engineering, PKNU. His research interests include circuits and systems, high-frequency measurement, sensor systems, image and signal processing with wavelet and adaptive filters, and communications theory.