

# **An Iterative Self-adaptive Algorithm to Impulse Noise Filtering for Color Images**

Shitong Wang<sup>1</sup>, Yueyang Li<sup>1</sup>, Fu-lai Chung<sup>2</sup>, and Min Xu<sup>1</sup>

<sup>1</sup> School of Information Engineering, Southern Yangtze University, Wuxi, China  
wxwangst@yahoo.com.cn, jsyueyangl@yahoo.com.cn,  
minmin528976@etang.com

<sup>2</sup> Department of Computing, Hong Kong Polytechnic University, Hong Kong  
cskchung@comp.polyu.edu.hk

## **Abstract**

Based on a simple impulse detector, an iterative self-adaptive algorithm to impulsive noise filtering for color images is presented in this paper. First, a simple but effective impulse detector is used in detecting the noise pixels in color images. Then, if a pixel is detected as a corrupted one according to the impulse detector, the proposed filter will select a suitable pixel in the predefined filter window to replace it, whereas the undistorted pixels are preserved under the filtering operation. The experimental results demonstrate that the proposed method outperforms other conventional multichannel filters in reducing impulsive noise and retaining edges and corners in color images. The distinctive advantage of our algorithm is its very simplicity but very good performance.

**Keywords:** Self-adaptive algorithm, color image processing, impulsive noise, multichannel filters.

## **1 Introduction**

Images are often corrupted by noise during the acquisition or transmission process. So noise cancellation/filtering is an important task in image processing, especially when the final product is used for edge detection, image segmentation, and data compression. In recent years, significant advances have been made in the development of noise attenuation techniques for multichannel images. As compared to gray scale images, each pixel of a color image is represented by three values that can be considered as a vector in a 3-D space, e.g., the RGB color space.<sup>1</sup>

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<sup>1</sup> Unless otherwise stated, the proposed filter operates on images in the RGB color space.

Image signals are composed of flat regional parts and abrupt changing areas, such as edges, which carry important information in visual perception. In the case of corruption by impulsive noise, nonlinear techniques seem to perform better than linear ones. In recent literature [1], [2], [3], a class of order-statistics multichannel filters based on reduced ordering (R-ordering) schemes to obtain order statistics has received considerable attentions. One version of R-ordering scheme is the aggregated distance, which is a summation of the distances between one vector and the others in a predefined filter window. Distinct distance measures develop different R-ordering filtering techniques, such as the *vector median filter* (VMF) [1], the *vector directional filters* (VDF) [2], and the *directional distance filter* (DDF) [3]. VMF uses  $L_1$  or  $L_2$  norm to order vectors according to their relative magnitude differences. The angular distance, which quantifies the orientation difference between two color vectors, can also be used as their distance measure. Therefore, the *basic vector directional filter* (BVDF) outputs the vector that minimizes the sum of the angles with all the other vectors. Combining VMF and VDF, Karakos *et al.* [3] proposed DDF by a generalized distance criterion to order the vectors inside the filter window. Although these conventional filters possess good impulsive noise attenuation characteristics, their performance is often accompanied with undesired processing of noise free image pixels, which results in edge and texture blurring.

In the case of impulsive noise removal, the aim of optimal filtering is to design noise reduction algorithms that would affect only corrupted image pixels, whereas the undistorted image pixels should be invariant under the filtering operation. Thus, an impulse detector can be employed to classify each pixel in the noisy images as noise or not prior to filtering. For example, in [4], a median and a weighted median based impulse detectors are introduced to determine whether a pixel is corrupted by impulsive noise or not. If the central pixel of the filter window is found to be corrupted by noise, it is replaced by the median filter output; otherwise, it is unchanged. Various switching median filters using different impulse detection approaches based on multiple center-weighted median filters with different center weights [5] and edge detection kernels [6] have been proposed.

In this paper, we present an iterative self-adaptive algorithm to impulsive noise filtering for color images based on a simple but effective impulse detector. Before filtering, the detector is first utilized to find out all pixels that are considered as noisy in the testing color image. If a pixel is detected as a corrupted one, the proposed filter will select a suitable pixel in the filter window centered around the noisy pixel to replace it. Otherwise, it remains unchanged. The new filter can be easily implemented and our experimental results indicate that the proposed filter has the ability of noise attenuation and edges or details preservation.

## 2 Basic Concepts about Multichannel Images

An 8-bit digital multichannel image  $\mathbf{I}$  with size  $r \times c$  in the RGB color space is represented by a matrix (of vectors) defined by

$$\mathbf{I} = \begin{bmatrix} \mathbf{x}_{11} & \mathbf{x}_{12} & \cdots & \mathbf{x}_{1c} \\ \mathbf{x}_{21} & \mathbf{x}_{22} & \cdots & \mathbf{x}_{2c} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{x}_{r1} & \mathbf{x}_{r2} & \cdots & \mathbf{x}_{rc} \end{bmatrix} = \left[ \mathbf{x}_{ij} \right]_{r \times c} \quad (1)$$

where  $\mathbf{x}_{ij} = [x_{ijR}, x_{ijG}, x_{ijB}]^T \in \{0, 1, 2, \dots, 255\}^3$  denotes a  $3 \times 1$  column vector pixel located at position  $(i, j)$  in  $\mathbf{I}$ , and  $x_{ijR}$ ,  $x_{ijG}$  and  $x_{ijB}$  denote the components in R, G and B channels, respectively. The superscript  $T$  denotes the matrix transpose.

An impulse detector window with size  $N_D = (2\zeta + 1)^2$  and a predefined filter window with size  $N_F = (2\tau + 1)^2$  ( $\zeta, \tau = 1, 2, \dots$ , and thus  $N_D$  and  $N_F$  are assumed odd) cover on the image  $\mathbf{I}$  at position  $(i, j)$  and can be represented by matrix  $\mathbf{W}_D[\mathbf{x}_{ij}]$  and  $\mathbf{W}_F[\mathbf{x}_{ij}]$ , respectively.  $\mathbf{x}_{ij}$  is the central vector pixel in the impulse detector window  $\mathbf{W}_D[\mathbf{x}_{ij}]$  or the filter window  $\mathbf{W}_F[\mathbf{x}_{ij}]$ . By using the row-major method, e.g., on signal set  $\mathbf{W}_F[\mathbf{x}_{ij}]$ , the observed sample matrix can be represented by

$$\mathbf{W}_F[\mathbf{x}_{ij}] = (\mathbf{x}_{i-\tau, j-\tau}, \mathbf{x}_{i-\tau, j-\tau+1}, \dots, \mathbf{x}_{ij}, \dots, \mathbf{x}_{i+\tau, j+\tau-1}, \mathbf{x}_{i+\tau, j+\tau}). \quad (2)$$

For convenience, the subscript pair  $ij$  in eq.(2) can be substituted by a scalar running index,  $l = (i-1) \times r + j$ . Hence, eq.(2) can be rewritten as

$$\mathbf{W}_F^{(l)} = (\mathbf{x}_1^{(l)}, \mathbf{x}_2^{(l)}, \dots, \mathbf{x}_{N_F}^{(l)}) \quad (3)$$

where  $N_F$  is the number of pixels in the filter window with size  $(2\tau + 1)^2$ , and  $\mathbf{W}_F^{(l)}$  is the filter window centered around the pixel  $\mathbf{x}^{(l)}$  (i.e.,  $\mathbf{x}_{ij}$ ). For example, we consider a  $3 \times 3$  filter window centered around  $\mathbf{x}^{(l)}$ , so eq.(3) can be described as

$$\mathbf{W}_F^{(l)} = (\mathbf{x}_1^{(l)}, \mathbf{x}_2^{(l)}, \dots, \mathbf{x}_9^{(l)}) . \quad (4)$$

In one channel, e.g., R channel, a  $3 \times 3$  filter window centered around  $x_R^{(l)}$ , which is the component in R channel of pixel  $\mathbf{x}^{(l)}$ , can be described as

$$W_F^{(l)} = (x_{1R}^{(l)}, x_{2R}^{(l)}, \dots, x_{9R}^{(l)}) \quad (5)$$

### 3 Impulsive Noise Model for Multichannel Images

In a gray scale image, the impulsive noise, such as *salt and pepper* noise, usually corrupts images by replacing some of the pixels of the original image with new pixels having luminance values near or equal to the minimum or maximum of the allowable dynamic luminance range with equal probability. So the gray scale images corrupted by impulsive noise with probability of occurrence  $p$  can be described as follows,

$$I' = \begin{cases} x, & \text{with probability } 1 - p \\ n, & \text{with probability } p \end{cases} \quad (6)$$

where  $I'$  denotes the impulsive noise corrupted image,  $x$ 's are the noise free pixels, and  $n$ 's are the noisy pixels whose luminance values are equal to or near the maximum or minimum of the allowable dynamic range with equal probability (i.e.,  $p/2$ ).

However, the impulsive noise model in the multichannel images is different from it in the gray scale setting. In this paper, all noisy images are generated by MATLAB 6.x, each channel of which is corrupted independently with *salt and pepper* (impulsive) noise. For example, if a multichannel image  $\mathbf{I}$  is distorted by 10% impulsive noise, each channel of  $\mathbf{I}$  is corrupted by 10% impulsive noise independently, i.e., about 10 percent of signals of each channel are replaced with new signals having luminance values near or equal to the minimum or maximum of the allowable dynamic luminance range with equal probability 5%.

### 4 A Simple but Effective Impulse Detector

According to the noise model in previous section, an impulse detector can be devised based on the fact that all impulses are outliers, i.e., the largest or the smallest ones among the signals of each channel. Thus, we detect corrupted pixels in the three channels of the images independently. In a channel, e.g.,  $R$  channel, we sequentially select the moving impulse detector window  $W_D[x_{ijR}]$  (the central signal of  $W_D[x_{ijR}]$  is  $x_{ijR}$ ) and then find out whether  $x_{ijR}$  is the maximum or minimum in  $W_D[x_{ijR}]$ . If  $x_{ijR}$  is the maximum or minimum, it is assumed to be corrupted. Otherwise, it is noise free. Mathematically, it can be denoted as

$$f_{ijR} = \begin{cases} 1, & \text{if } x_{ijR} = \max(W_D[x_{ijR}]) \text{ or } x_{ijR} = \min(W_D[x_{ijR}]) \\ 0, & \text{else} \end{cases} \quad (7)$$

where  $\max(W_D[x_{ijR}])$  and  $\min(W_D[x_{ijR}])$  are the maximal and minimal value in the window  $W_D[x_{ijR}]$ , respectively. The noise distribution corresponding to the R channel of the corrupted color image  $\mathbf{I}$  can be represented by a binary matrix  $F_R = [f_{ijR}]_{r \times c}$ . If  $f_{ijR}$  equals 1, it implies that the pixel  $x_{ijR}$  is corrupted by noise; otherwise ( $f_{ijR}$  equals 0),  $x_{ijR}$  is noise free. According to the impulse detection algorithm mentioned above, we can obtain the noise distribution  $F_G$  and  $F_B$  corresponding to the G and B channels of the corrupted color image  $\mathbf{I}$ , respectively. In this way, we can locate all noisy pixels in the corrupted color image  $\mathbf{I}$ .

Owing to the possible mistakes the impulse detector might make, two scenarios have to be taken into account. First, a number of the noisy pixels may be not detected, i.e., these noisy pixels may be considered as noise free pixels by the impulse detector. Second, some noise free pixels may be misdected, i.e., these noise free pixels may be considered as noisy pixels by the impulse detector.

Based on the detecting method mentioned above, our experiment indicates that all noisy pixels in the image will be detected by the impulse detector. On the other hand, there are a small number of noise free pixels that are considered as noisy by the detector. The number of the noise free pixels, which are misdected as noisy pixels, will decrease as the size of the detector window increases and the noise density increases. Therefore, we can enlarge the detector window to reduce the possibility that some of original pixels are considered as noisy. In general, in order to improve the performance of the detector and consider the computational complexity simultaneously, when the impulsive noise density is less than 10%, the size of the detector window should be  $9 \times 9$ ; otherwise, a  $7 \times 7$  detector window is recommended. It can be easily concluded from the experiment that the proposed impulse detector, despite its simplicity, is effective in detecting the noise pixels in color images.

## 5 The Iterative Self-adaptive Algorithm to Impulse Noise Filtering

In this paper, each testing noisy image is generated by MATLAB 6.x, each channel of which is corrupted independently with impulsive *salt and pepper* noise. The proposed filter works in three channels of the image independently. In a channel, e.g., R channel, if  $x_{ijR}$  is noisy indicated by the binary flag map  $F_R$ , it will be replaced by one suitable pixel in the predefined filter window  $W_F[x_{ijR}]$  centered around  $x_{ijR}$ . Otherwise,  $x_{ijR}$  will remain unchanged.

In the construction of our new filter, the following similarity function  $s(d)$  is introduced here [7], [8].

$$s(d) = \exp(-\beta d) \quad (8)$$

where the parameter  $\beta \in (0, \infty)$ , which has been discussed in detail in [7]. The argument of the function  $s(d)$

$$d = |x_i - x_j| \quad (9)$$

is the distance between two pixels  $x_i$  and  $x_j$  in the filter window.  $|\cdot|$  denotes  $L_1$  norm. The similarity function  $s(d)$  shows that the similarity between two pixels is small if the distance between them is large. In the extreme, the similarity between two pixels with the same gray scale value is 1; the similarity between pixels with far distance intensities is 0.

Let us now assume that in one channel, e.g., R channel,  $x_R$  is the center pixel (which is noisy) in the filter window  $W_F$  and the pixel  $x_{iR}$  ( $i = 1, 2, \dots, m$ ) is noise free one surrounding  $x_R$ . The filter works as follows. The central pixel  $x_R$  is replaced by that  $x_{iR}$ , which maximizes the sum of similarities between all its noise free neighbors. In other words,  $i_* = \arg \max T_{iR}$

$$T_{iR} = \sum_{j=1}^m s(|x_{iR} - x_{jR}|), \quad i, j = 1, 2, \dots, m, \quad i \neq j \quad (10)$$

where  $T_{iR}$  is the total similarity function which is a sum of all values of similarities between pixel  $x_{iR}$  and its noise free neighbors.

We define  $\mathbf{I}^{(0)}$  and  $F_k^{(0)}$  ( $k = R, G, B$ ) represent the noisy testing image and the binary flag map obtained by the impulse detector, respectively.  $\{\mathbf{I}^{(1)}, \mathbf{I}^{(2)}, \dots, \mathbf{I}^{(n)}, \dots\}$  is the output image set and  $\{F_k^{(1)}, F_k^{(2)}, \dots, F_k^{(n)}, \dots\}$  is the binary flag map set.  $\mathbf{I}^{(n)}$  and  $F_k^{(n)}$  denote the filtering image and the binary flag matrix after  $n$  iterations, respectively.

The impulse detector is first employed to produce the binary flag map  $F_k^{(0)}$ . The filter works in three channels of the image independently. The filtering procedure can be described as follows:

Step 1.

Set  $n = 1$ , where  $n$  denotes the number of iteration. Set  $\mathbf{I}^{(n)} = \mathbf{I}^{(n-1)}$ ,  $F_k^{(n)} = F_k^{(n-1)}$ . Set  $l$  to the first location of the noisy pixel according to the binary flag map  $F_k^{(n-1)}$ .

Step 2.

Obtain the  $l$ -th observed sample matrix  $W_F^{(l)}$  from image  $\mathbf{I}^{(n-1)}$  (If there is no noise free pixel in the filter window  $W_F^{(l)}$ , set  $l$  to the next location of the noisy pixel according to  $F_k^{(n-1)}$ ).  $T_{ik}$  ( $k = R, G, B$ ) is calculated by equation (10) and  $i_* = \arg \max T_{ik}$ .

Step 3.

In image  $\mathbf{I}^{(n)}$ , the center pixel  $x_k^{(l)}$  of the filter window  $W_F^{(l)}$  is replaced by  $x_{i_*k}^{(l)}$ . In the binary flag matrix  $F_k^{(n)}$ , set  $f_k^{(l)}$  to 0 after pixel  $x_k^{(l)}$  is changed. If  $l$  equals to the last location of the noisy pixel according to the binary flag map  $F_k^{(n-1)}$ , go to Step 4. Otherwise, set  $l$  to the next location of the noisy pixel according to  $F_k^{(n-1)}$ , and go to Step 2.

Step 4.

The filtering process stops when each pixel of the binary flag matrix  $F_k^{(n)}$  equals to 0, i.e., all noisy pixels of image  $\mathbf{I}^{(n)}$  have been filtered.  $\mathbf{I}^{(n)}$  is taken as the final output of the filter. Otherwise, set  $n = n + 1$ ,  $\mathbf{I}^{(n)} = \mathbf{I}^{(n-1)}$ ,  $F_k^{(n)} = F_k^{(n-1)}$ , and  $l$  equals to the first location of the noisy pixel according to the binary flag map  $F_k^{(n-1)}$ , and then go to Step 2.

Obviously, the algorithm presented in this paper can be easily realized. For an image corrupted by impulsive noise, because not all pixels are corrupted, the new algorithm keeps the original value if a pixel is noise free while the corrupted pixel is replaced by one of its noise free neighbors. In this way, the new algorithm replaces the pixel only when it is really noisy, and meanwhile, it preserves the original undistorted image structures.

## 6 Experimental Results

Several experimental results are presented in this section to demonstrate the power of our new filtering algorithm. The color image Lena, with size  $256 \times 256$ , is employed and it is shown in Fig.2(a). All noisy images are generated by MATLAB 6.x, each channel of which is corrupted independently with impulsive *salt and pepper* noise. The filter window in our experiments is  $3 \times 3$ . Two quantitative measures, MAE and PSNR, are used to assess the filtering performance. The corresponding calculations are recalled as follows.

$$MAE = \frac{\sum_{l=1}^{r \times c} |\mathbf{x}^{(l)} - \hat{\mathbf{x}}^{(l)}|}{3 \times r \times c} \quad (11)$$

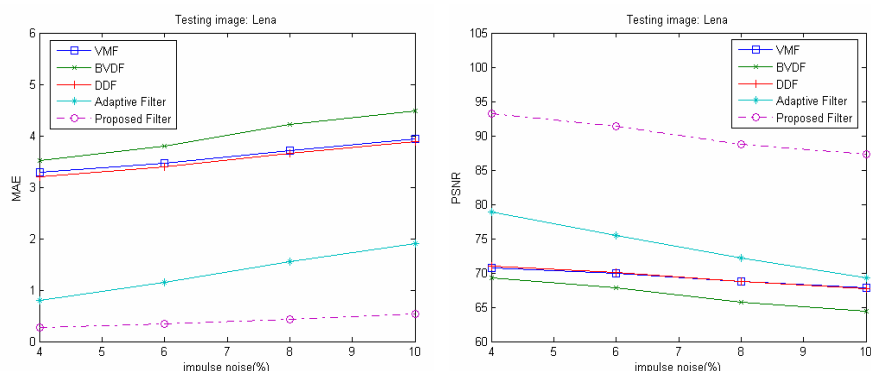
$$PSNR = 20 \times \log_{10} \left( \frac{255}{RMSE} \right) \quad (12)$$

where

$$RMSE = \sqrt{\frac{\sum_{l=1}^{r \times c} \|\mathbf{x}^{(l)} - \hat{\mathbf{x}}^{(l)}\|}{3 \times r \times c}}, \quad (13)$$

$\mathbf{x}^{(l)}$  and  $\hat{\mathbf{x}}^{(l)}$  represent the original and the estimated image vector-valued pixels, respectively.  $\|\cdot\|$  and  $|\cdot|$  denote the  $L_2$  and  $L_1$  norm, respectively.

The performance of the proposed filter is compared with that of the other conventional multichannel filters, namely *vector median filter* (VMF) [1], *basic vector directional filter* (BVDF) [2], *distance and directional filter* (DDF) [3], and the adaptive filter in [7]. The results are reported in Fig.1. The testing image, Lena, is corrupted by impulsive noise ranging from 4% to 10%. Figs.1 show the filtering performance of the proposed filter compared with the other four filters. From the Fig.1, it is obvious that the proposed filter, in terms of the two quantitative measures, clearly outperforms the conventional filters.



**Fig. 1.** Filtering performance of the proposed filter compared with the other four filters. The testing image Lena is corrupted by impulsive noise ranging from 4% to 10%

In addition to the quantitative evaluation presented above, a qualitative evaluation is necessary since the visual assessment of the processed images is ultimately the best subjective measure of the effectiveness of any method [9]. Fig.2 depicts the superior filtering results of the new filter for the image Lena corrupted by 4% impulsive noise, in comparison with the



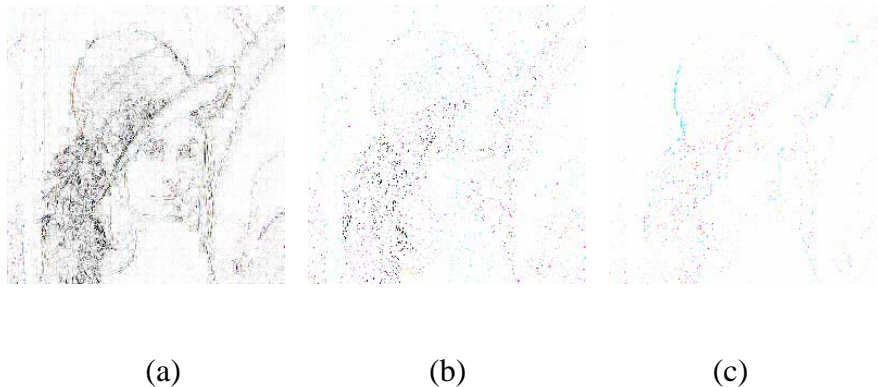
three multichannel filters. Fig.3 shows the absolute difference between the original and each filtered image for the corrupted image Lena. Note that the RGB values are multiplied by factor 5 to provide clearer comparison. It can be seen that the difference between the original and the new filtered image has the minimal magnitude, which implies that the ability of preserving edges and details of the new algorithm is quite well.



**Fig. 2.** Filtering results for the testing image Lena. (a) Original image. (b) Image corrupted by 4% impulsive noise. (c) Restored image using VMF. (d) Restored image using BVDF. (e) Restored image using the adaptive filter in Ref. [7]. (f) Restored image using the proposed filter

## 7 Conclusion

The new filtering algorithm proposed in this paper indeed improves the popular nonlinear, multichannel filters in reducing impulsive noise in color images. Based on a simple but effective impulse detector, the new filter only affects corrupted image pixels, whereas the noise free pixels are invariant under the filtering operation. In this way, the new filter outperforms the conventional multichannel filters and achieves better capability of preserving the original structure of the image. Besides, very easy implementation is another distinctive advantage.



**Fig. 3.** The effect of preserving edges and details of the proposed filter as compared with VMF and the adaptive filter in Ref. [7]: (a)-(c) the absolute difference between the original and filtered image ((a) VMF. (b) The adaptive filter in Ref. [7]. (c) The proposed filter.). Note that the RGB values are multiplied by factor 5 to provide clearer comparison

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**Shitong Wang**, received the M.S. degree in computer science from Nanjing Aeronautical University, Nanjing, P.R.China, in 1987. From then on, he was with dept. of computer science and engineering, EastChina Shipbuilding Institute, China, where he was lecturer in 1988, associate professor in 1992, full professor in 1995. He visited Royal Holloway College, London University, from 1995 to 1996; Bristol University, from 1998 to 1999; HongKong University of Science and Technology for six months in 2001, HongKong Polytechnic Univ., five times during 2002--2005, totally for 12 months; Hiroshima International Univ. in Japan for several months in 2003. Now, he is with dept. computer science and technology, Southern Yangtze University, WuXi, China. He has published numerous papers in international/national journals and has authored 6 books. His research interests include neuro-fuzzy systems, AI, pattern recognition/image processing and their applications.



**YueYang Li**, Ph.D student.



**Korris F.L. Chung**, associate Professor in computer science. He earned his Ph.D from Chinese University of HongKong in 1994. He has published numerous papers in international journals including IEEE Trans. Fuzzy systems, IEEE Trans. SMC, IEEE Trans. Multimedia. His research interests include Fuzzy AI, pattern recognition/image processing and their applications.

**Min Xu**, Postgraduate student.