

Switching Median Filter Based on Iterative Clustering Noise Detection

Chingakham Neeta Devi¹, Keisham Pritamdas²

¹Department of Computer Science and Engineering, National Institute of Technology, Manipur, India

²Department of Electronics and Communication Engineering, National Institute of Technology, Manipur, India

Abstract: *In this paper, a switching median filter incorporated with an iterative clustering based noise detection algorithm that effectively restores images corrupted with impulse noise is proposed to improve the performance of switching based median filters. The proposed filter mechanism involves a noise detection algorithm for image restoration that detects corrupted pixels by classifying the pixels into three pixel clusters iteratively. If the pixel in consideration falls under the middle cluster in the last iteration, the pixel is classified as uncorrupted otherwise it is detected as corrupted. Corrupted pixels go through median filtering leading to restoration of the noisy image effectively while uncorrupted pixels remain unperturbed. Experimental results show that the proposed filter provides appreciable quality restored images preserving important details of the image.*

Keywords: Impulse noise, noise model, noise detection, image restoration, switching median filters.

1. Introduction

Images are often corrupted by impulsive noise that leads to the degradation of the quality of the image. Corruption by impulse noise is normally due to the errors generated in noisy sensors and communication channels [1], [2]. The subsequent image processing operations such as image compression, image edge detection, image segmentation and object tracking etc. might get worse performances if the noise exists in the input image with high noise density. Therefore, detecting noise and replacing the noise pixel with an appropriate value is an important work for image processing. One of the most popular impulse noise removal nonlinear filters is the median filter [3] which is well known for eliminating the noise in the smooth regions in image. But in the detail regions such as edge and texture, the median might smear the detail. Because the typical median filter is uniformly applied across an image, it is prone to modify both noisy pixels and noise-free good pixels producing a number of artifacts. Various median based impulse noise filters have already been proposed in [4], [5], [6], [7] to overcome mentioned problems.

2. Related Work

In the field of image processing, nonlinear median filters have attracted much attention of image processing researchers in the past decades. In 1995, Hwang and Haddad [4] proposed an Adaptive Median Filter. The Adaptive Median Filter (AMF) preserves the sharpness of the image while having a variable window size for removing impulse noise while preserving sharpness. Wang and Zhang [6] proposed a progressive switching median filter (PSMF) in 1999. The PSMF incorporates a switching scheme. Along with the switching scheme, the filtration method progress through several iterations to denoise the corrupted image.

Center weighted median filter [7] performs image restoration to a satisfiable level for slightly corrupted images but gives poor results for highly corrupted images.

Conventional median filters substitute the pixel in consideration with the median value without considering whether the pixel is corrupted or not. And as such valuable image details are lost as noise-free pixels also gets replaced by the median value leading to image quality degradation. In order to overcome the disadvantage of the conventional median filters, a switching scheme is employed to decide when to apply the median filter as described in [4], [5], [6], [7], [8], [9]. In switching based median filters, the main issue is design of an efficient noise detection algorithm which distinguishes noisy and noise-free pixels. Sun and Neuvo [4] proposed the first switching algorithm where corrupted pixels are passed through the median filter while the values of the uncorrupted pixels remain intact by making them pass through the identity filter.

The main idea behind switching median filter is the identification of corrupted and uncorrupted pixels. A feasible solution to this is to implement impulse-noise detection algorithm prior to filtering and classify the pixels as corrupted or uncorrupted. The corrupted pixels are then passed to the filtering process while the uncorrupted pixels remain undisturbed. The first stage is for noise detection, while the second stage is for noise suppression. Ng et. al. [8] proposed the boundary discriminative noise detection algorithm to determine whether the current pixel is a corrupted pixel or a noise-free pixel. According to the noise detection algorithm two boundaries that forms three clusters- lower intensity impulse noise, uncorrupted pixels and higher intensity impulse noise are determined and each pixel is classified whether it is corrupted or uncorrupted. Then, the corrupted pixel is passed through median filter to perform the restoration process. Sorted Switching Median Filter (SSMF) proposed by [9] consists of three phases- detecting stage, the sorting stage and the filtering stage, the SSMF.

This paper presents an iterative clustering based switching median filter that preserves image details while effectively suppressing impulse noise. The proposed filter mechanism involves a noise detection algorithm that detects the center

pixel within the considered window as corrupted or uncorrupted. The noise detection algorithm detects between corrupted and non-corrupted pixels by classifying the pixels into three clusters iteratively. If the pixel in consideration falls under the middle cluster in the last iteration, the pixel is classified as uncorrupted otherwise it is detected as corrupted. Corrupted pixels go through median filtering leading to restoration of the noisy image effectively. Experimental results show that the proposed filter provides good quality restored images preserving important details of the image.

The paper is divided into five sections as follows. Section 1 as already seen gives a brief introduction. Section 2 describes how and why a switching median filter is important. Section 3 describes the noise models. Section 4 describes proposed impulse noise detection algorithm and switching median filter. Section 5 presents the experimental results showing the performance evaluation of the proposed filter. Section 6 concludes the paper giving a brief summary of the paper.

3. Noise Models

Noise models are associated with detection and filtration of impulse noise. Various noise models can be developed but the general models [8] used normally are described in this section. Two of the noise models have been implemented and used for carrying out the evaluation process of the proposed filter. In all the models, for each image pixel at location (x,y) , with intensity value $i_{x,y}$, $n_{x,y}$ represents the corresponding pixel of the noisy image; p and p_i represent the noise densities.

1) *Noise Model 1*: In this first model, noise is modelled as salt and pepper noise with equal probability where pixels are randomly corrupted by fixed extreme values 0 and 255. The probability density function is as follows:

$$f(n) = \begin{cases} \frac{p}{2}, & n = 0 \\ 1 - p, & n = i \\ \frac{p}{2}, & n = 255 \end{cases} \quad (1)$$

Here, p represents the total noise density.

2) *Noise Model 2*: The difference between Noise Model 2 and the Noise Model 1 is that each pixel might be corrupted with unequal probabilities by either salt or pepper. The probability density function is:

$$f(n) = \begin{cases} \frac{p_1}{2}, & n = 0 \\ 1 - p, & n = i \\ \frac{p_2}{2}, & n = 255 \end{cases} \quad (2)$$

and total noise density p is given by $p_1 + p_2$.

3) *Noise Model 3*: Another realistic approach to modeling impulse noise is to adopt two fixed ranges of length l each, and then the noise could take any values within the range. The probability density function will be:

$$f(n) = \begin{cases} \frac{p}{2l}, & 0 \leq n < l \\ 1 - p, & n = i \\ \frac{p}{2l}, & 255 - l < n \leq 255 \end{cases} \quad (3)$$

where p is the total noise density.

4) *Noise Model 4*: The only difference with Model 3 is that densities of low and high intensity noise are unequal as given:

$$f(n) = \begin{cases} \frac{p_1}{2l}, & 0 \leq n < l \\ 1 - p, & n = i \\ \frac{p_2}{2l}, & 255 - l < n \leq 255 \end{cases} \quad (4)$$

and the total noise density is p given by $p_1 + p_2$.

4. Proposed Algorithm

4.1 Noise Detection Algorithm

Before an image is filtered, its pixels need to be classified as noisy or noise-free. The following proposed algorithm detects whether the current pixel centred at the window is corrupted or not and is somewhat similar to [6], [8]. The original image is transformed in this noise detection process into image sequences $a_1^i, a_2^i, \dots, a_n^i$ where a_i^i are the image sequences generated where a_i^i denotes the pixel centred at coordinate $i(x,y)$ and bitmap sequence b_i^i of same dimension as a_i^i is obtained at each iteration n . All the values of Bitmap sequence b_i^i are set to 0's. The bitmap sequences $b_1^i, b_2^i, \dots, b_n^i$ are generated using the following steps:

- 1) Consider an 11 x 11 window centred on the current pixel in consideration.
- 2) The pixels in the window are sorted in ascending order in Vector V whose elements are denoted by v_i where i ranges from 0 to n .
- 3) The median M is computed for the sorted vector V .
- 4) Again, the median M_l for the lower half of the vector V is calculated.
- 5) The maximum intensity difference between the pairs of pixels of the lower half till M_l is computed. The lower bound B_l is given by the corresponding pixel.
- 6) Similar to step (4) and step (5), M_h is computed and upper bound B_h is found out using the same procedure.
- 7) If the current pixel falls within the values of B_l and B_h , it is considered as uncorrupted and b_i^i is set to 0 else it is classified as corrupted and b_i^i is set to 1.

The above algorithm steps groups the pixels into three clusters $\{v_0, B_l\}$, $\{B_l, B_h\}$ and $\{B_h, v_n\}$. Thus, the bitmap b_i^n at iteration n has values 0 for the pixels which fall in the middle cluster which are classified as uncorrupted group of pixels while the pixels that fall in the other two clusters are termed as corrupted and b_i^n values are set to 1.

Image a_i^{n-1} is operated using the bitmap b_i^n generated in the above steps to generate its next image sequence a_i^n using the given relation

$$a_i^n = \begin{cases} m_i^{n-1}, & \text{if } b_i^{n-1} = 1 \\ a_i^{n-1}, & \text{if } b_i^{n-1} = 0 \end{cases} \quad (5)$$

where m_i^{n-1} is the median of the window centred at $i(x,y)$, over the noisy image a_i^{n-1} .

The steps described in the algorithm are repeated for $n=1, 2, 3$ to generate a final image sequence a_i^3 and a corresponding bitmap b_i^3 indicating the corrupted and non corrupted pixels. For colour RGB images, bitmap sequences for each channel are used and the algorithm is run for each channel.

4.2 Switching Median Filtering

The previous section described about noise detection algorithm which plays a major role in designing a switching based median filter. After the detection of the corrupted pixel, filtering process is carried out. The filtering part is discussed in this section.

The final bitmap b_i^3 is checked for getting the information whether the pixel is corrupted or not at. After the pixel has been classified as noisy, the pixel is passed through median filter with a maximum window size of 5×5 . The median value of a window for gray level images of size W can be calculated using

$$O_{x,y} = \text{med} \{ I_{x-s,y-t} \mid (s,t) \in W \} \quad (6)$$

O represents the output pixel and I represent pixels that participated in the ranking of pixels to compute the median within the window W .

Considering colour images, for each pixel vector v_i , its L_1 -norm distances with respect to other pixel vectors is computed individually and summed together by using

$$S_i = \sum_{j=1}^N \|v_i - v_j\| \quad (7)$$

for $i = 1, 2, 3, \dots, N$

Each corrupted pixel is replaced the vector median corresponding to the minimum value of S_i .

Another point considered is the non-inclusion of the corrupted pixel for ranking while calculating the median value. That is, if the current pixel is classified as corrupted, it will be excluded from the process of ranking; that is only noise-free pixels within the window are considered for the ranking process. This provides better results leading to less distortion.

5. Experimental Results

For the experimental purpose in order to simulate the performance of the proposed filter, Noise Model 1 has been used. The first step in image restoration is detection of noisy pixels. The simulations of the proposed filter give the following Miss Detection percentage and False Alarms shown in table 1. It can be seen from the table that the proposed filter gives low miss detection and false alarms.

The images show the simulation results which will be discussed in details later in this section. Noise Model 1 using equation (1) has been used for the injection of salt and pepper noise to the original image shown in figure 1. The images after the injection of the noise at various density levels 20,40,70,80 using Noise Model 1 have been shown in the figures. The corresponding filtered images after the detection of corrupted pixels and subsequent median filtering are shown side by side of the noisy images.

Table 1: Miss Detection and False Alarm for the Proposed Iterative Clustering Noise Detection based Switching Median Filter using Noise Model 1

Noise Percentage	Miss Detection	False Alarm
10	0	0
20	0	2
30	4	9
40	7	11
50	14	13
60	18	17
70	25	20
80	38	34
90	65	43

The images with low noise densities 20% and 40% are filtered very effectively as shown in figure 1. The proposed filter provides very good result for low noise densities. Images injected with high noise densities 70% and 80% shown in figure 2 give satisfiable filtered results as can be seen from the images. The evaluation of the performance of the proposed filter is done in terms of Peak Signal to Noise Ratio (PSNR), using the formula

$$PSNR = 10 \log_{10} \left(\frac{255^2}{MSE} \right) \text{ dB} \quad (8)$$

where Mean Square Error (MSE) is

$$MSE = \frac{1}{XY} \sum_{i=1}^X \sum_{j=1}^Y (f_{i,j} - o_{i,j})^2 \quad (9)$$

Here, X and Y denote the total number of image pixels in the horizontal and vertical dimensions; $f_{i,j}$ and $o_{i,j}$ represent the original and filtered pixels of the image respectively.

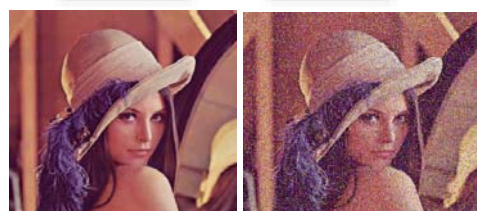




Figure 1: Original image alongwith noise induced images with noise density 20% and 40% and their subsequent median filtered image side by side

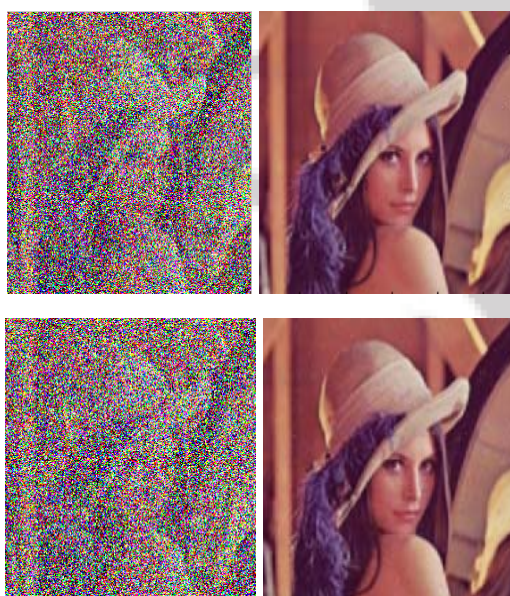


Figure 2: Noise induced images with noise density 70% and 80% and their subsequent median filtered image side by side

The PSNR values obtained for the proposed Iterative Clustering Switching Noise detection based Median Filter using Noise Model 1 where the noise density ranges from low density to high density is shown in table 2. From the values shown, it can be said that the proposed filter provides good results in comparison with traditional median filter (MF) and Progressive Switching Median Filter (PSMF).

Table 2: Psnr Values for Different Noise Densities Using Noise Model 1

Noise Model 1			
Noise Density (%)	PSNR (Db)		
Salt/ Pepper	MF	PSMF	Proposed Filter
10/10	25.66	28.39	27.420
15/15	21.86	25.52	24.803
20/20	18.21	22.49	20.761
25/25	15.04	19.13	18.054
30/30	11.08	12.10	14.503
35/35	9.93	9.84	10.034
40/40	8.68	8.02	7.651
45/45	6.65	6.57	5.012

6. Conclusion

In this paper, an iterative clustering noise detection based switching median filter is proposed. The proposed filter incorporates a noise detection algorithm which effectively classifies pixels as corrupted or uncorrupted. The proposed filter provides low miss detection and false alarm values. After the classification of the pixel as corrupted or uncorrupted, the corrupted pixel goes through median filtering process leading to restoration of the noisy image. The uncorrupted pixel remains undisturbed preserving the important image details. The proposed filter is compared with conventional median filter and psmf filter, the results are found to be appreciable in comparison with them. The proposed filter provides good quality results as shown in the image figures.

References

- [1] T. Chen, H.R. Wu, "Space variant median filters for the restoration of impulse noise corrupted images", IEEE Transactions on Circuits and Systems-II: Analog and Digital Signal Processing Vol. 48, No. 8, pp 784-789, 2001.
- [2] R. Lukac, B. Smolka, K. Martin, K.N. Plataniotis, A.N. Venetsanopoulos, "Vector filtering for color imaging", IEEE Signal Processing Magazine Vol. 22, No. 1, pp 74-86, 2005.
- [3] RC Gonzalez, RE Woods, "Digital Image Processing", Third Edition, Pearson, 2009.
- [4] T. Sun, Y. Neuvo, "Detail-preserving median based filters in image processing", Pattern Recognition Letters, Vol. 15, No.4, pp 341-347, 1994.
- [5] H. Hwang, R.A. Haddad, "Adaptive median filters: new algorithms and results", IEEE Transactions on Image Processing Vol.4, No.4, pp 499-502, 1995.
- [6] W. Zhou, Z. David, "Progressive switching median filter for the removal of impulse noise from highly corrupted images", IEEE Transactions on Circuits Systems-II: Analog and Digital Signal Processing Vol.46, No.1, pp 78-80, 1999.
- [7] T Chen, HR Wu, "Adaptive impulse detection using center-weighted median filters", IEEE Signal Process Let, Vol. 8, No. 1, pp 1-3, 2001.
- [8] P.E. Ng, K.K. Ma, "A switching median filter with boundary discriminative noise detection for extremely corrupted images", IEEE Transactions on Image Processing Vol 15, No. 6, pp 1506-1516, 2006.
- [9] Shi-Jinn Horng, Ling-Yuan Hsu, Tianrui Li, Shaojie Qiao, Xun Gong, Hsien-Hsin Chou, Muhammad Khurram Khan, "Using Sorted Switching Median Filter to remove high-density impulse noises", Elsevier Journal of Visual Communication and Image Representation, Vol.24, No. 7, pp 956-967, 2013.

Author Profile



Chingakham Neeta Devi completed her B.E from Manipur Institute of Technology, Manipur and M.Tech from The Oxford College of Engineering, Bangalore. She is currently working as Assistant Professor in Computer Science and Engineering Department of National Institute of Technology, Manipur.



Keisham Pritamdas completed his B.E from PGP College of Engineering and Technology and M.E from Sri Krishna College of Engineering, Chennai. He is currently working as Assistant Professor in Electronics and Communication Engineering Department of National Institute of Technology, Manipur.



IJSR