PERFORMANCE ANALYSIS OF MEDIAN FILTERING APPROACHES FOR IMAGE DE-NOISING IN THE PRESENCE OF IMPULSIVE NOISE

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Abstract

Impulsive noise is also known as salt and pepper noise. Impulsive noise is found in situations where quick transients such as faulty switching take place during image acquisition. Standard median filter has been established as reliable method to remove this noise without harming the edge and image overall contrast. However, the major problem of standard Median Filter (MF) is that the filter is effective only at low noise densities. In our proposed method, adaptive median filter and modified median filtering approaches are implemented and these are compared with different methods to find median for the given data called median of ungrouped data (MUD) also known as standard median filter approach, median of grouped discrete frequency data distribution (MGDFD) and median of grouped continuous frequency data distribution (MGCFD). Our proposed methods performs better in removing low to high density impulsive noise with detail preservation and gives better visual quality and better peak signal to noise ratio(PSNR).

Keywords: Image de-noising, MUD: median of ungrouped data, MGDFD: Median of grouped discrete frequency data, MGCFD: Median of grouped continuous frequency data. PSNR: Peak Signal to Noise Ratio.

1. INTRODUCTION

Impulsive noise is caused by malfunctioning of photo sites in imaging area, faulty memory locations in physical memory, or transmission in a noisy channel. Two common types of impulse noise are the salt-and-pepper noise and the random-valued noise. For images corrupted by salt-and-pepper noise (respectively, random-valued noise), the noisy pixels for a gray level image can take only the maximum (255) and the minimum (0) values (respectively, any random value) for an 8-bit gray scale image generated with the same probability. Let us consider an original image ‘f’ and ‘g’ is the noisy version of it. Therefore the gray level values of ‘g’ at any location (i, j) is modeled as

$$g(i, j) = \begin{cases} 0, \text{ with probability p/2} \\ 255, \text{ with probability p/2} \\ f(i, j), \text{ with probability 1-p} \end{cases}$$

There are many papers on the de-noising of images corrupted by impulse noise. The standard median filter [1] is one of the most popular nonlinear filtering techniques to de-noise the image when the noise level is less than 50% of the original pixels in an image. However, when the noise level is over 50%, the edge details of the original image will not be preserved by standard median filter. Adaptive median filter [3] performs well at medium noise densities but it fails as the window size increases in the case of high noise densities leads to blur the image details. Switching median filter [4] based on the minimum absolute value of four convolutions obtained using one dimensional Laplacian operator. A two phase scheme using regularization method [5] used to restore images show significant improvement compared to those restored by using nonlinear filters or regularization methods. A novel switching median filter method [6] called boundary discriminative noise detection proposed for effectively de-noising extremely corrupted images. The decision based algorithms [7] are also proposed but making robust decision is very difficult and these filters will not take into account the local features as a result of this details and edges may not be recovered satisfactorily when the noise level is high. A modified decision based asymmetrical trimmed median filter [8] algorithm proposed for the restoration of gray scale images that are corrupted by high density salt and pepper noise.

In this paper, we used MUD, MGDFD and MGCFD [2] methods to find median of the given data distribution for implementing adaptive median filter and modified median filter approaches. In the MGCFD method, we considered class length of 4 and the class interval starts from 0-4, 5-9 and so on and ends with 255-259 so that 52 different intervals are formed. We used MUD method as a default method whenever it is not possible to find median with MGDFD and MGCFD methods. The outline of the paper is as follows. Our method of de-noising scheme is presented in Section 2. Simulations and conclusion are presented in Sections 3 and 4 respectively.

2. OUR METHOD OF IMPLEMENTATION

Algorithm 1: Adaptive Median Filter approach [1]

Step 1: Read noise image $g(i, j)$.

Step 2: Initialize the de-noised image as the size of the noisy image with all zeros.

Step 3: If $0 < g(i, j) < 255$ then these pixels are considered as uncorrupted pixels and copy to de-noised image at their respected positions and considered them as processed pixels.

Step 4: Initialize processing window (mask) size $w = 3$ *and* $w\max = 11$.

Step5: Select a wxw sub image where centre pixel g_{ij} is the processing element which is not processed already. Copy all the pixel gray levels of this sub image to a row matrix(S) to compute gray level minimum $(Z\min)$, gray level maximum $(Z\max)$ and gray level median $(Zmed)$ of 'S'.

Step 6: If $Z\min < Zmed < Z\max$ does not satisfy then leave it as unprocessed pixels then go to step 8.

Step 7: if $Z\min < g_{ij} < Z\max$ then g_{ij}, else $Zmed$ is considered as a noise free pixel and copy it to the de-noised image at its respected position and treat this as a processed pixel.

Step 8: If the entire pixels are not processed using window size 'w', then go to step 5 by considering another unprocessed pixel.

Step 9: Increment window size by 2. If window size $w \le w\max$ then go to step 5 and continue the process.

Step 10: Copy $Zmed$ of all unprocessed pixel values to de-noised image at their respected positions.

Above procedure repeated for calculating median of 'S' in step 5 by using MUD, MGDFD and MGCFD approaches.

Algorithm 2: Modified Median Filtering

As mentioned in step 3 [8], If all the elements in the vector are noisy (0 or 255 gray value), then replacing the central pixel intensity value with mean of its values in the neighborhood leads to wrong pixel gray level values in the de-noised image. We proposed new approach in order to overcome this problem in this paper.

Step 1: Read noise image $g(i, j)$.

Step 2: Initialize the de-noised image as the size of the noisy image with all zeros.

Step 3: Consider sub image of size w=3, start processing first pixel g_{ij}, If $0 < g_{ij} < 255$ then g_{ij} is considered as an uncorrupted pixel and go to step 8.

Step 4: Grow sub image of size wxw by considering g_{ij} as the center pixel.

Step 5: Copy all the pixel gray levels of a sub image to a row matrix(S) except the center pixel.

Step 6: if 'S' contains all 0's or 255 s or both then increase w by 2 and go to step 4.

Step 7: Calculate un symmetric trimmed median of 'S'.

Step 8: Copy this value to the de-noised image at its respected position and treat this as a processed pixel.

Step 9: If the entire pixels are not processed then go to step 3 by considering another unprocessed pixel.

Above procedure repeated for calculating median of 'S' in step 7 by using MUD, MGDFD and MGCFD approaches.

3. SIMULATIONS

We have taken two test images 'lena.jpg' and 'house.jpg'. The dynamic range of gray levels are in the range [0 255]. In the simulation, images are corrupted with salt (with value 255) and pepper (with value 0) noise with equal probability. The de-noising methods proposed in algorithm1 and algorithms 2 are tested at noise densities in the range 20% to 90%. De-noising performances are quantitatively measured by the peak signal-to-noise ratio (PSNR). PSNR measurements for 'lena.jpg' image using algorithm1 and algorithm 2 for median methods MUD, MGDFD and MGCFD at various noise densities are given in Table 1&2 and comparative plots are shown in Fig.1 and Fig.2 respectively. Similarly, PSNR measurements for 'house.jpg' image using algorithm1 and algorithm 2 for median methods MUD, MGDFD and MGCFD at various noise densities are given in Table 3&4 respectively. MGCFD method of median approach gives good PSNR value for algorithm 1 and MUD method gives good PSNR value for algorithms 2. PSNR analysis of algorithm 1 with MGCFD and algorithm 2 with MUD measurements for 'lena.jpg' image and 'house.jpg' images at various noise densities and comparative plots are shown in Fig.3 and Fig. 4 respectively. The peak signal-to-noise ratio (PSNR) is the ratio between a signal's maximum power and the power of the signal's noise.

$$MSE = \frac{1}{MN}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}[f(x,y) - f^{'}(x,y)]^2 \text{ , } PSNR = 10\log_{10}(255^2 / MSE)$$

where $f(x, y)$ and $f^{'}(x, y)$ are original image and de-noised images of size MxN respectively.

Table 1: Comparision of PSNR values of the algorithm 1 for 'lena.jpg' image at noise density of 20%, 40%, 60%, 70 %, 80% and 90%.

Noise Level (%)	Adaptive Median filter(Median of Ungrouped Data) (MUD)	Adaptive Median filter (Median of Grouped Discrete Frequency Data) (MGDFD)	Adaptive Median filter(Median of Grouped continuous Frequency Data) (MGCFD)
20	32.10	33.3175	33.35
40	27.9865	28.4414	28.4436
60	24.65	25.10	25.39
70	22.4645	22.99	23.6358
80	18.28	18.78	19.98
90	11.31	11.58	13.32

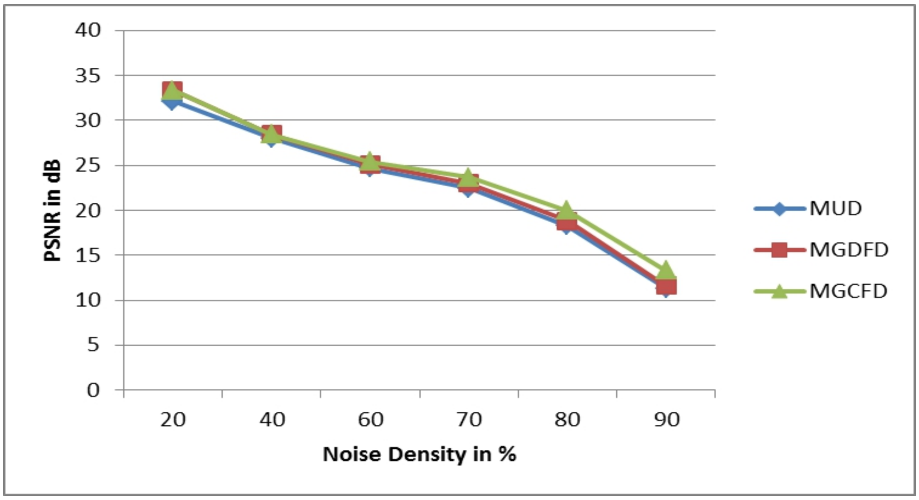

Fig. 1: Comparision graph of Median techniques at different noise densities for 'lena.jpg' image using algorithm1

Table 2: Comparision of PSNR values of the algorithm 2 for 'lena.jpg' image at noise density of 20%, 40%, 60%, 70 %, 80% and 90%.

Noise Level (%)	Adaptive Median filter(Median of Ungrouped Data)	Adaptive Median filter (Median of Grouped Discrete Frequency Data)	Adaptive Median filter(Median of Grouped continuous Frequency Data)
20	35.57	34.85	34.84
40	31.28	30.44	30.36
60	28.11	27.20	27.11
70	26.46	25.53	25.47
80	24.73	23.99	23.99
90	22.44	21.90	21.92

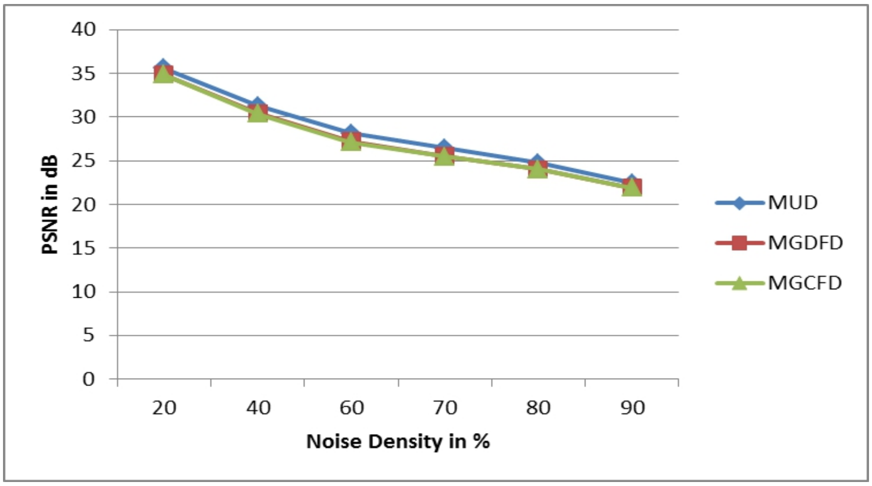

Fig. 2: Comparision graph of Median techniques at different noise densities for ‘lena.jpg’ image using algorithm 2

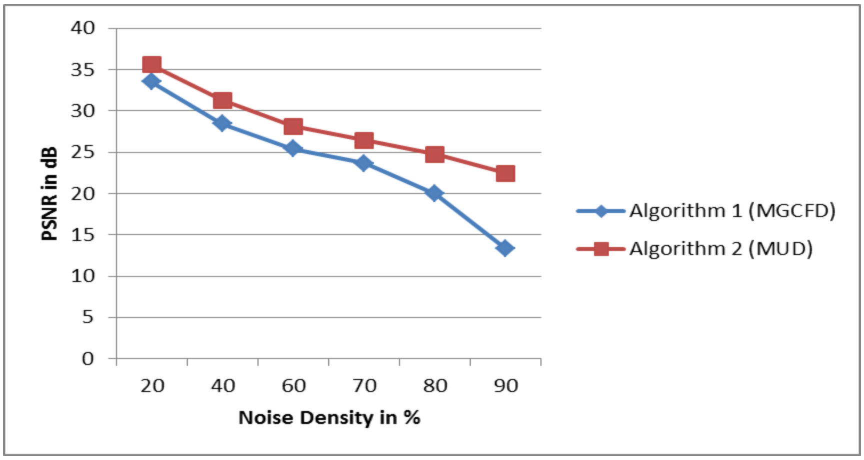

Fig. 3: Comparison graph of algorithm 1 & algorithm 2 at different noise densities for ‘lena.jpg’ image

Table 3: Comparision of PSNR values of the algorithm 1 for ‘house.jpg’ image at noise density of 20%, 40%, 60%, 70 %, 80% and 90%.

Noise Level (%)	Adaptive Median filter(Median of Ungrouped Data)	Adaptive Median filter (Median of Grouped Discrete Frequency Data)	Adaptive Median filter(Median of Grouped continuous Frequency Data)
20	32.80	34.60	34.62
40	29.15	29.69	29.80
60	26.11	26.64	26.99
70	24.15	24.69	25.46
80	19.60	20.06	22.06
90	11.52	11.80	15.32

Table 4: Comparision of PSNR values of the algorithm 2 for 'house.jpg' image at noise density of 20%, 40%, 60%, 70 %, 80% and 90%.

Noise Level (%)	Adaptive Median filter(Median of Ungrouped Data)	Adaptive Median filter (Median of Grouped Discrete Frequency Data)	Adaptive Median filter(Median of Grouped continuous Frequency Data)
20	36.80	35.90	34.65
40	32.09	31.22	30.60
60	29.24	28.50	28.02
70	27.71	27.63	26.73
80	26.17	25.60	25.50
90	23.8	23.28	23.30

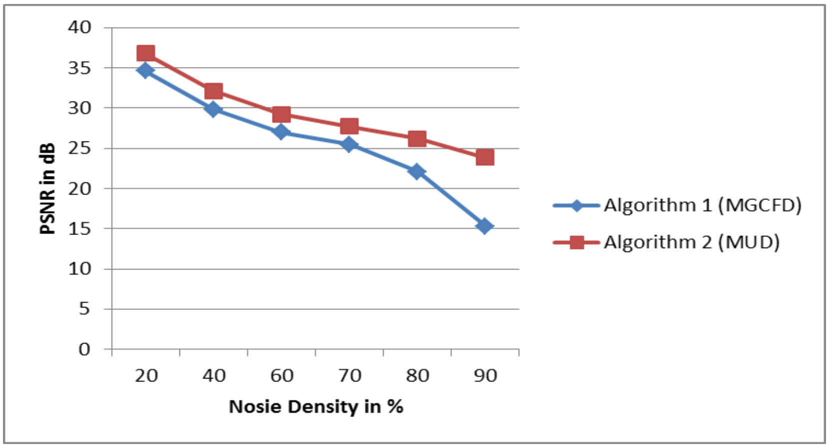

Fig. 4: Comparison graph of algorithm 1 & algorithm 2 at different noise densities for 'house.jpg' image

4. Conclusion

In this paper, we proposed our image de-noising scheme and also compared this scheme using with various methods of finding median for the given data distribution. In the adaptive median filtering approach median of grouped continuous frequency data distribution method gives good result comparatively other two methods because of the presence of impulsive data in the sorted array. In the modified median filtering approach median of ungrouped data method gives better results because of calculation of the median for the non impulsive data. Experimental results show that our method performs much better than adaptive median-based filters even at very high noise densities. The de-noised image can also be obtained by using various hybrid combinations of these outputs. The six outputs of algorithm 1 and algorithm 2 can also be used as initial population to work with soft computing techniques like PSO, Bacterial foraging and other swarm optimization methods to improve further visual quality and better PSNR ratio.

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