

**Comparative Analysis of Various denoising algorithms**¹Deepti, ²Dr. Nipin Gupta, ³Dr. Pankaj Gupta, ⁴Dr. Deepak Goyal^{1,2,3,4}Vaish College of Engineering

Abstract: Image Processing & Image De-noising plays a crucial role in copious applications. The image de-noising technique is to improve both visual appearance & interpretability of an image & also provide better output which is used in further application in other automated image processing techniques by suppressing the unwanted information (noise & blur). The proposed work compares different de-noising algorithms (such as Median Filter (MF), Decision Based Median Filter (DBMF), Progressive Switched Median Filter (PSMF), Un-trimmed Median Filter (UMF)) based on the various parameters such as PSNR (Peak Signal-to-Noise Ratio), MSE (Mean Square Error), IEF (Image Enhancement Factor), MAE (Mean Absolute Error). The result is preferred on grayscale as well as on colored images for different noise levels. From the results it is concluded that the UMF reduces the noise effectively.

Keywords: MF, DBMF, PSMF, UMF.

Introduction

Image de-noising is effectively used to reduce noise & to restore the image while keeping its features intact (e.g. edges etc.). The de-noising technique depends on the various types of noise which corrupts the image which can be categorized as Gaussian noise, Gamma noise, Uniform noise, Impulse noise, Rayleigh noise, Speckle noise. These types of noise have their own probability density functions & are quantified by the percentage of corrupted pixels presents in image[1]. De-noising technique improves the Quality but Information retrieved from the noisy image by using different types of de-noising filter models. Usually, there are two types of filter models i.e. linear filter & non-linear filter model. The main benefits of linear noise removing filter models is the speed but limitations of these models is that they are not able to preserve edges in an efficient manner i.e. edges, that are recognized as discontinuities in image, are tarnished out. Non-linear filter models can handle edges in a much better way [2]. The proposed work presents a review on different filters applied to restore the image that is corrupted by impulse noise. The impulse noise is of two types: Random-Valued Impulse Noise (RVIN) in which noise is randomly distributed over the entire image and probability of occurrence of any gray level value as noise will be same and Fixed-Valued Impulse-Noise (FVIN),[6] in which the noise appears as black and white spots on the distorted image. The FVIN is also called as salt-&-pepper noise (SPN) can be modeled as:

$$(X_{ij}) = \left\{ \begin{array}{ll} A_{ij} & , \text{ probability } q \\ (0,255) & , \text{ probability } 1-q \end{array} \right\}$$

Where 'A_{ij}' & 'X_{ij}' denotes the intensity value of original & noisy image at coordinate (i, j) resp. & 'q' is the noise-density of the corrupted pixels.

The rest paper has been organized as follows manner, Section(II) describes the Median Filter, Section(III) contains Decision-based-median Filter, Section(IV) discuss the Progressive-Switched-median Filter, Section(V) describes the Untrimmed-median Filter, Section(VI) presents results & discussion, conclusions are finally drawn in section(VII).

Section II: Median Filter

Median filter (MF), a non-linear filter is most commonly used to eliminate impulse noise from images. It has an important advantage of preserving edges in an image while removing noise, that may occur due to random bit error in the communication channel [2]. The basic concept of MF is to slide a window of size W×W (where W is odd) through the

image, pixel-by-pixel and replace the value of center element with the median of its neighboring pixels. The Algorithm of MF is shown in fig.1:

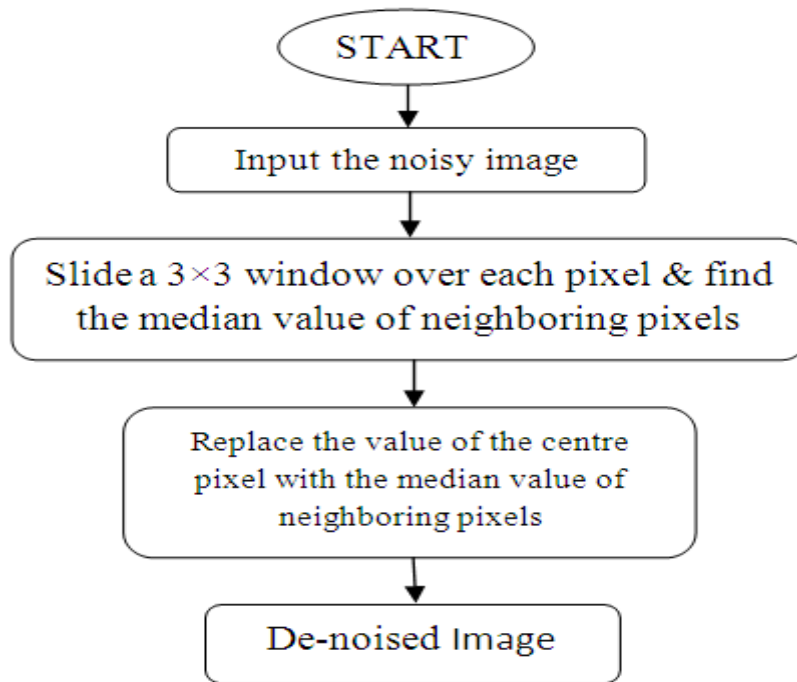


Figure1

Figure (2) shows the median value $F_m(i, j)$ for the center pixel $f(i, j)$ at position (i, j) of the selected window is expressed as:

$$F_m(i, j) = \text{med}[f(i-1, j-1), f(i-1, j), f(i-1, j+1), f(i, j-1), f(i, j), f(i, j+1), f(i+1, j-1), f(i+1, j), f(i+1, j+1)]$$

$f(i-1, j-1)$	$f(i-1, j)$	$f(i-1, j+1)$
$f(i, j-1)$	$f(i, j)$	$f(i, j+1)$
$f(i+1, j-1)$	$f(i+1, j)$	$f(i+1, j+1)$

Figure 2: Neighborhood of a pixel centered at (i, j) in a window of size (3×3)

However MF is successful only at low noise densities & smoothes the image. The another disadvantage of this filter modifies both the noisy as well as noise free pixels during the filtering results in blurring and distorted features in the resultant de-noised image.

Section III: Decision Based Median Filter

When the noise level is over 50% MF is unable to fully extract noise and fails to conserve the edges in an image. To overcome the problem of Median filter the DBMF algorithm was proposed in literature. The DBMF involves two steps: noise detection and noise filtering. DBMF first detects the noisy pixels iteratively through multiple phases and then replaces the detected noisy pixels with the median value. Replace

The processing of the DBMF is given below:

Step1: Select 2-D window of size $W \times W$ ($W=\text{odd}$) & Assume that X_{ij} be the processing pixel centered at position (i, j) in the selected window.

Step2: If $\{0 < X_{ij} < 255\}$ then $\{X_{ij}$ is noise less & left unchanged $\}$

Step3: If $\{\{X_{ij}=0 \text{ or } X_{ij}=255\} \&\& \{\text{all surrounding elements have same value}\}\}$ then $\{X_{ij}$ is an information pixel $\}$
 Else $\{X_{ij}$ is the noisy pixel $\}$

Step4: For noisy pixel

Case (1): If {selected portion of window have all the elements 0's or 255's} **then** {replace X_{ij} with the mean value of the elements in the selected window}

Else {remove 255's and 0's & find the median value of the remaining elements in the selected window & replace X_{ij} value with the median value}

Step5: If {corrupted pixels in a selected window $\geq 50\%$ (so there is a possibility to get corrupted median of selected window)} **then** {median can be replaced by nearest information pixel}

Step6: Repeat steps 1 to 5 until all the pixels value in the entire image are processed.

This algorithm gives good results at low noise variance & it eliminate the noise effectively but distort the image at high noise variance that is above 0.8. The main drawback of this filter is the repeated replacement of neighboring pixel produces "streaking effect" & results in distorted features in the resultant de-noised image.

Section IV: Progressive Switching Median Filter

In PSMF both the noise detector and the noise removal filter are applied gradually in an iterative manner. The noisy pixel (corrupted pixel) that are processed in the current iteration are used to help in the processing of the other pixels in ensuing iterations. The most beneficial part of such kind of filter is that some corrupted elements located in the middle of large noise blotches can also be properly detected and then filtered out[5].

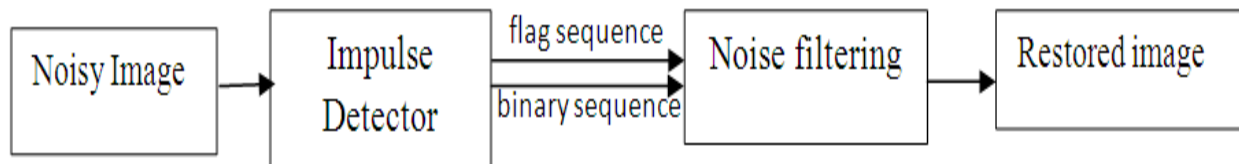


Fig.1 shows the working stages

Therefore, better restoration results are predicted, especially when the images are highly influenced by impulse noise.

Section V: Untrimmed median Filter

The Untrimmed Median Filter (UTMF) is used to prevail over the drawbacks of DBMF, where the processing pixel checks (whether the pixel is corrupted or not) before trimming in the selected window of order $W \times W$. In the processing window ($W \times W$) if the pixels are not corrupted; no trimming is applied & trimming is carried out only on the corrupted pixels on either side of the sorted window in an un-symmetrically manner[4].

Step1: All the pixels values of the selected window (3×3) are sorted in either increasing or decreasing order.

Step2: Noise Detection: let X_{ij} be the processing pixel

Case (1): if {Min. gray level $< X_{ij} <$ Max. gray level} **then** { X_{ij} is noise-free pixel & left unchanged }

Case (2): if { $X_{ij} = (0's \text{ or } 255)$ } **then** { X_{ij} is noisy pixel }

Step3: Then find the median value from the remaining pixels values in the selected window (3×3).

Step4: Now replace the noisy pixel value with the median value.

Step5: Repeat steps 1 to 4 until all the corrupted pixels in the entire image are processed.

This algorithm gives better results at high noise variance that is up to 0.7 & it does not distort the image as in DBMF. But the main drawback of UMF is that it does not completely remove the effect of noise at very high variance.

Section VI: Simulation Results & Discussion

To validate the de-noising methodologies an image 'Almighty' of size 256×256 is considered. The performance of the different algorithm is evaluated with comparable study for various existing filters. The figure (a), (b), (c), (d), (e) & (f) shows the original image, noisy image & de-noised image obtained using MF, DBMF, PSMF, UMF & didn't give better results in comparison with results of UMF.



Fig.(a) original
Image

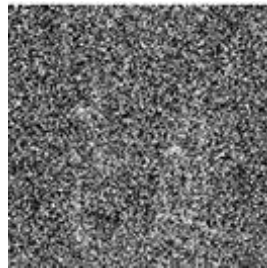


Fig.(b) Noisy image
(at noise_var.= 0.7)

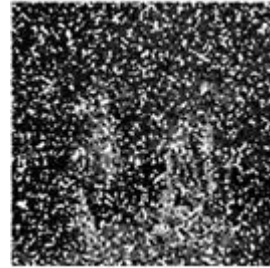


Fig.(c) Denoised image
(by using MF)



Fig.(d) Denoised image
(by using PSMF)



Fig.(e) Denoised image
(by using DBMF)



Fig.(f) Denoised image
(by using UMF)

Table1: comparison of MSE for diff. filters

MSE : (low)				
Var	MF	DBMF	UMF	PSMF
0.1	95.7332	10.7604	19.8373	43.5124
0.2	172.9031	34.5894	35.9040	87.1884
0.3	499.6310	40.4159	39.9132	152.0820
0.4	1.2493e+03	75.4470	70.6658	252.4109
0.5	2.5902e+03	112.7016	106.4590	576.6068
0.7	8.7201e+03	276.8003	228.2210	3.4692e+03

Table2:comparison of PSNR for diff. filters

PSNR: (high)				
Var.	MF	DBMF	UMF	PSMF
0.1	28.3202	37.8125	35.1560	31.7447
0.2	25.7528	34.2233	32.5794	28.7262
0.3	21.1443	32.0653	33.3556	26.3100
0.4	17.1641	29.3544	29.9053	24.1097
0.5	13.9974	27.6115	28.1113	20.5220
0.7	8.7256	23.7091	24.4799	12.7286

Table3: comparison of MAE for diff. filters

MAE: (low)				
Var.	MF	DBMF	UMF	PSMF
0.1	3.0802	0.4974	0.4988	1.4302
0.2	3.8469	1.0201	1.2808	2.7004
0.3	5.8266	1.5596	1.5549	4.2554
0.4	9.9542	2.3253	2.1807	6.1296
0.5	17.2338	3.1879	2.9308	9.4415
0.7	48.3203	7.6461	7.6430	26.9228

Table4:comparison of IEF for diff. filters

IEF: (high)				
Var.	MF	DBMF	UMF	PSMF
0.1	28.8918	226.1554	220.8590	58.7469
0.2	28.4986	200.5407	185.4137	55.9557
0.3	14.9069	177.8161	177.9563	49.3175
0.4	7.8575	129.2753	137.4508	39.0106
0.5	4.6893	107.9518	196.3249	21.7408
0.7	1.9709	62.5917	109.5964	4.9377

Table (1-4) gives the objective comparison of these filters for different values of noise densities. The results of UMF gives lower (MSE, MAE) & higher (PSNR, IEF) and its performance is superior than other filters at high noise variance.

Section VII: CONCLUSION

In this work, different filters have been used as a tool for eliminating low and high density salt-and-pepper noise with edge preservation in digital images. As a visual inspection; for low noise variance up to 0.3, all the filters performs well in eliminating the FVIN For noise variance above 0.4 & 0.5 the only the DBMF and UMF gives good results. At noise variance (0.7 onwards), the DBMF removes the effect of noise but produce streaking effect in the image. Both visual and quantitative results are demonstrated that the UMF filter is very effectual for SPN removal in images at high noise variance.

References

- [1] ^aGovindaraj.V, ^bSengottaiyan.G: International Journal of Science, Engineering and Technology Research (IJSETR), Volume 2, Issue 2, February 2013
- [2] Pawan Patidar, Sumit Shrivastava: Image De-noising by Various Filters for Different Noise; International Journal of Computer Applications (0975 – 8887); Volume 9– No.4, November 2010
- [3] Hassan M. ElKamchouchi, Ahmed E. Khalil, Samy h. Darwish: Removal of High Density Impulsive Noise in Image Using Non Linear Filters; 2015 Seventh International Conference on Computational Intelligence, Modelling and Simulation, 2166-8523/15 \$31.00 © 2015 IEEE
- [4] S. Esakkirajan, T. Veerakumar, Adabala N. Subramanyam, and C. H. PremChand: Removal of High Density Salt and Pepper Noise Through Modified Decision Based Unsymmetric Trimmed Median Filter; IEEE SIGNAL PROCESSING LETTERS, VOL.18, NO.5, MAY2011
- [5] Zhou Wang and David Zhang: Progressive Switching Median Filter for the Removal of Impulse Noise from Highly Corrupted Images; IEEE TRANSACTIONS ON CIRCUITS AND SYSTEMS—II: ANALOG AND DIGITAL SIGNAL PROCESSING, VOL. 46, NO. 1, JANUARY 1999
- [6] Charles Bonchelet "Image Noise Models". in Alan C. Bovik. Handbook of Image and Video Processing, 2005.

Authors

First Author- Deepti, M.Tech, Student, Vaish College of Engineering, Rohtak, HR

E-mail: deeptigarg429@gmail.com

Second Author- Nipin Gupta, H.O.D, Vaish College of Engineering, Rohtak, HR

E-mail: callnipin@gmail.com

Third Author- Pankaj Gupta, Assistant Professor, Vaish College of Engineering, Rohtak, HR

E-mail: pankajgupta.vce@gmail.com

Fourth Author- Deepak Goyal, Associate Professor, Vaish College of Engineering, Rohtak, HR

E-mail: deepakgoyal.vce@gmail.com