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An Effective Noise Adaptive Median Filter for Removing High Density Impulse Noises in Color Images

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Article Info	ABSTRACT
	Images are normally degraded by some form of impulse noises during the acquisition, transmission and storage in the physical media. Most of the real time applications usually require bright and clear images, hence distorted or degraded images need to be processed to enhance easy identification of image details and further works on the image. In this paper we have analyzed and tested the number of existing median filtering algorithms and their limitations. As a result we have proposed a new effective noise adaptive median filtering algorithm, which removes the impulse noises in the color images while preserving the image details and enhancing the image quality. The proposed method is a spatial domain approach and uses the 3×3 overlapping window to filter the signal based on the correct selection of neighborhood values to obtain the effective median per window. The performance of the proposed effective median filter has been evaluated using MATLAB, simulations on a both gray scale and color images that have been subjected to high density of corruption up to 90% with impulse noises. The results expose the effectiveness of our proposed algorithm when compared with the quantitative image metrics such as PSNR, MSE, RMSE, IEF, Time and SSIM of existing standard and adaptive median filtering algorithms.

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1.   INTRODUCTION

Image Processing is one of the fast rising fields in the area of computer science and engineering. The growth of this field has been superior by the technological advancements in digital computing, processors, multimedia data processing and mass storage devices. All fields which were operating on the analog signals are now increasingly converting into the digital systems for their ease of use, reliability and flexibility. Image processing has been extensively applied in the area of medical, photography, film industry, remote sensing, traffic control, astronomy, police investigation, business, industry, transport traffic-control, military target analysis, and manufacturing automation and control. Image pre-processing techniques such as image enhancement, image restoration and object recognition are used to process the image depending on the type of interference that has caused the degradation [1].

Noises in the digital images are modelled as three standard categories, they are additive noises, multiplicative noises and random impulse noises. Most of the digital images are normally corrupted by impulse noise during communication [2]. The two common impulse noise types are random-valued noise and salt and pepper noise. In the random impulse noise model, image pixels are randomly corrupted by two fixed extreme values, 0 and 255 (for gray-scale image), generated with the same probability that is *P* is noise density, then *P1* is the noise density of salt (*P/2*) and *P2* is the noise density of pepper (*P/2*). Instead of two

fixed values, images may be corrupted by two fixed ranges that appear both ends with length of m each respectively, that is [0,m] denotes salt and [255-m,255] denotes pepper. Here for noise density *P, P1=P2=P/2*. Another model with only low intensity impulse noise and only high intensity impulse noise also affect the digital images, that is *P1≠ P2*. The salt and pepper noises are saturated values that take maximum and minimum allowed values of intensities. In this paper we are merely considering impulse noise with *P1= P2*.

In any signal processing system, filtering is an essential part which involves estimation of a signal degraded in most cases by impulse noise. Impulse noises are mostly caused during the process of image acquisition, transmission through communication media and storage in the physical devices. Several filtering techniques have been developed over the past several decades for various applications. The type of noise factor and intensity of the noise that has degraded the image is also taken into consideration before the filter is developed and used.

The techniques for filtering image noises can be divided into two broad categories: spatial domain filtering and frequency domain filtering. The spatial domain filtering techniques are based on the direct manipulation of the image pixels where as the frequency domain filtering techniques have to do with modifying the Fourier transform of the interested image. The spatial domain filtering is further subdivided into linear filtering and nonlinear filtering. In linear filtering, a single pixel with very unrepresentative value can significantly affect the mean value of all the pixels in its neighbourhood and when the filter neighbourhood stand across an edge the filter will interpolate new values for pixels on the edge and so will blur that edge. This may be a problem if sharp edges are required in the output. These problems are rectified by the nonlinear filtering. Order statistic filters are nonlinear spatial filters whose response is based on ordering the pixels contained in the image area encompassed by the filter and then replacing the value of the center pixel with that value determined by the ranking result [2]. The best known order-statistic nonlinear filter is the median filter.

A number of methods have been introduced to remove impulse noise from digital images. The standard median filter and mean filter are used to reduce salt & pepper noise and Gaussian noise respectively. When these two noises exist in the same image, use of only one filtering method cannot achieve the desired result.

Vector Median Filter (VMF) is a simple rank selection filter that identifies and eliminates the fixed and random valued impulse noises in the digital images. In this filtering algorithm, the vector of pixels in a specified window is ranked on the basis of sum of the distances to other vector of pixels in the another window. The center vector of pixel is declared as noisy if its rank is bigger than a predefined rank and its distance from a nearby healthy vector pixel is bigger than the predefined threshold. The noisy pixel is replaced with the vector median. The threshold mechanism for detection of noisy pixel and replacing it with vector median is suitable for images with noises up to 50% of noise level. Even though VMF is noise adaptive filter, it is not suitable for higher noise densities [3].

Standard Median Filter (SMF) is also a simple rank selection filter that attempts to eliminate impulse noise by changing the luminance value of the center pixel of the filtering window with the median of the luminance values of the pixels contained within the window. Although the SMF is simple and provides a reasonable noise removal performance, it removes thin lines and blurs image details even at low noise densities. Furthermore, it has no adaptation for varying noise levels for a reliable median signal. This method affects the information of the uncorrupted true pixel by taking median itself impulse value [4].

Weighted Median Filter (WMF) and Center Weighted Median Filter (CWMF) are modified median filters introduced to preserve the image details of all the spatial positions by giving more extra weight to the appropriate pixels of the filtering window. These filters have been proposed to avoid the inherent drawbacks of the standard median filter by controlling the trade-off between the noise suppression and detail preservation. But their detail preservation on images is limited as the extra weight given to a corrupted signal can increase noise of the highly corrupted digital image and there is no adaptation towards the varying noise ratio for choosing the weight and neighborhood of a particular signal [5].

The Progressive Switching Median Filter (PSMF) is obtained by combining the median filter with an impulse detector and an impulse corrector. The impulse detector aims to determine whether the center pixel of a given filtering window is corrupted or not. If the center pixel is identified by the detector as a corrupted pixel, then it is replaced with the output of the median filter, otherwise, it is left unchanged. In the case where majority of the edge pixels in the image are polluted by impulse noise, filtering is incomplete because the switching median filter only works on the centre value of the window and even for the smallest sized window, 3×3, it is not possible to have an edge pixel in the centre of the sliding window. In impulse correction phase, an iterative correction process follows where only the corrupted pixels are replaced by the median of uncorrupted pixels of a window identified in the latest detection iteration. The flag is reset, means, the next iteration uses the modified image and the modified flag image as inputs [6].

In this paper, we propose a spatial domain method using the overlapping kernel window to filter the image based on the selection of neighboring pixel values and obtaining an efficient median per window position. For each window position a median is found for selective pixels in the window depending on the condition we pursued. The median is tested, and if it is unaffected by impulse noise, it is confirmed as the effective median.

The organization of this paper is as follows: Section 2 discusses related works which involve removal of impulse noises using adaptive median and some of its derivative filters. Section 3 presents the proposed effective noise adaptive median filtering algorithm. The comparison of proposed filter with other non-linear filters by using quantitative metrics is given under the heading of results and discussion in Section 4 and finally the paper is concluded with future direction in Section 5.

2. RELATED WORKS

In this section, we present a brief review of the adaptive median filtering algorithms. The adaptive median filters are non-linear ordered statistic digital filtering techniques which are normally used to reduce high density noises extremely in an image. It is one of the best windowing operators out of the many windowing operators like the mean filter, min and max filter and the mode filter.

Hwang et.al., proposed an Adaptive Median Filter (AMF) to eliminate the problems faced by the Standard Median Filter and Switching Median Filters. AMF changes its behaviour based on the statistical characteristics of the image inside the filter window. The performance of Adaptive filter is usually superior to non-adaptive counterparts. The improved performance is at the cost of added filter complexity. Mean and variance are two important statistical measures based on which adaptive filters can be designed. In practice this filter imposes a limit to the window size, S_{xy}. When this limit is reached while the selected median is an impulse, the impulsive noise remains in that window of the image. The adaptive median filter achieves good results in most cases, but even so, computation time is proportional to the degree of corruption of the image being filtered [4].

Rank Ordered Adaptive Median Filter (ROAMF) also proposed by Hwang, H. and Haddad, R.A., which keeps the image details of highly corrupted digital images by switching the filtering of only the corrupted signals with a mid-ranking value chosen from a neighborhood that varies adaptively with the quantum of impulse noise. AMF detects corrupted signals by checking them to be between minimum and maximum of the median detected neighborhood, it fetches a reliable median from an adaptively varying neighborhood for only the corrupted signals and works very well for all types of images up to 60% noise levels. The main limitation of this filter is that the impulse replacing median is not determined from uncorrupted pixels, impulse replacing median from a bigger window affects the image fidelity, unnecessary increase of window-size though uncorrupted pixels are in a smaller window and computationally this filter is costly [1], [4].

Akkoul et.al., proposed the Adaptive Switching Median Filter (ASMF), which uses decision and correction windows that are adaptive to effectively find impulse positions and signal restorers. The image fidelity of the restored outputs is better at higher and lower impulse noise ratios. This filter reduces unnecessary increase in window size and the impulse restoring value is from among the nearest reliable intensities which gives best possible restoration even in highly corrupted environment [9].

Decision Based Algorithms (DBAs) were introduced by both Srinivasan et.al., and Madhu et.al., with different approaches, which detect corrupted signals by checking them to be between minimum and maximum of the median detected neighborhood. Both fetch a reliable median from neighborhood for only the corrupted signals. Therefore, their approaches work efficiently well for all types of images up to 50% noise levels. The limitations such as improper analyze of impulse detection and the absence of valid median force their algorithms to replace the signal with previously restored value. These problems make the horizontal and diagonal streaks in restored images. Furthermore, these filters do not consider the preservation of image details [10], [11].

Aiswarya et.al., proposed the Decision Based Unsymmetric Trimmed Median Filter (DBUTMF) for removing high density impulse noises in images and videos, which overcome the problem of streaking effects in DBAs. In this algorithm the left and right extreame values of the stored array obtained from the 3×3 window are impulse values and are trimmed. The corrupted pixel is replaced by the median of the resultant array. Eventhough this approach is better than DBAs, it doesn't preserve the image details at higher noise densities [12],

3. PROPOSED EFFECTIVE NOISE ADAPTIVE MEDIAN FILTER(ENAMF)

In the proposed method, the size of the window is fixed, however, the effective median may be different from the value at the middle of the sorted pixel values. The proposed effective median filter is designed to diminish the problem faced by the standard median filter and other Adaptive Median Filters. The proposed algorithm is the modification of Decision Based Algorithm (DBA) of Srinivasan et.al. It restores the digital images corrupted at high or low impulse noise ratios by switching only the filtration of the corrupted image signals with a much reliable mid-ranking statistics value to keep up the signal content of the restored image. Furthermore the horizontal and diagonal streaks in the DBA is rectified in the proposed algorithm by restoring the correct pixel values from the neighboring pixels in the kernel window.
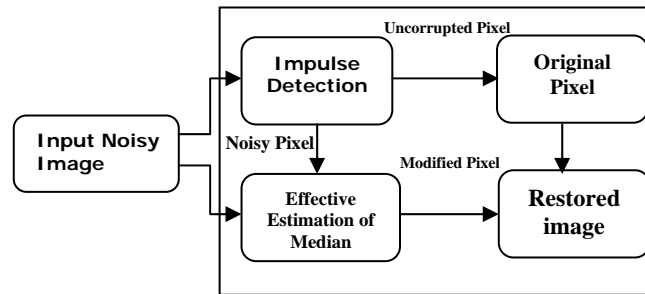

Figure 1. Block Diagram of Proposed method

The block diagram of proposed filter is shown in Figure 1 and explanatory steps of the proposed algorithm for the gray scale and color images are as follows.

3.1 Algorithm-1a
Input   : Gray Scale Image Img
Output : Denoised Image b

Step 1: Set sliding window size $W_{min}=3\times3$, noisy image a and restored image b
Step 2: Read the pixels from the window and store it in S
Step 3: Compute S_{min}, S_{max} S_{med} and Np
Step 4: If $S_{min}<a(i,j)<S_{max}$, where a(i,j) is the processing central pixel, then it is consider as uncorrupted pixel and retained. Otherwise go to step 5.
Step 5: If $S_{min} < S_{med} < S_{max}$, where S_{med} is the median value of S, then it is consider as corrupted pixel and replace b(i,j) by S_{med}. Otherwise go to step 6.
Step 6: If Np>=5 and b(i,j-1)=0, then it is consider as corrupted pixel and replace b(i,j) by S_{min}. If Np >= 5 and b(i,j-1)=255, then replace the corrupted pixel b(i,j) by S_{max}. Otherwise replace the b(i,j) by the mean value of previously processed pixels b(i-1,j) and b(i,j-1).
Step 7: If Np<5 then replace the b(i,j) by S_{med}.
Step 8: Repeat the above steps for all the pixels in the image

3.2 Algorithm-1b
Input: RGB Image Img
Output: Noise Filtered image MLFI

Step1: Input the RGB image Img = imread(<RGB Image>)
Step2: Split the image into three layers namely Red Channel, Green Channel and Blue Channel.
  MLI(0) = Red(Img)
  MLI(1) = Green(Img)
  MLI(2) = Blue(Img)
  MLI =∫ Red(Img)+Green(Img)+Blue(Img)
Step3: Take each layer and check for impulse noise in each pixels using 3×3 kernel window.
Step4: Apply the proposed effective noise adaptive median filter with an appropriate value from an accepted neighborhood to Red Channel and other set of values to Green and Blue Channels.
        MLF(I) = ENAMF(MLI(I)).

Step 5: Concatenate the filtered three channels MLFI = cat(MLF(i))
Step 6: Display the noise filtered color image

The two dedicated steps of the proposed filter are:
Step 1: Aadaptive detection of impulsive locations in three channels.
Step 2: Correction of the detected impulsive pixels with an appropriate value from an acceptable neighborhood from the window on three channels.

The proposed filter has adaptive detection of impulse noises that leads to become maximum signal extraction and impulse restoring value is from among the nearest reliable intensities give best possible restoration even in highly corrupted environment up to 90% noise level. The horizontal and diagonal streaks are very less when compared with other adaptive non-linear filters. The performance of the filtering process is quantified by using metrics such as Peak Signal to Noise Ratio (PSNR), Mean Square Error (MSE), Root Mean Square Error (RMSE), Time factor, Image Enhancement Factor (IEF) and the Structural Similarity Index (SSIM) that clearly show the betterment of our proposed effective nonlinear filter from other adaptive filters. The above said metrics are represented in equation (1) through (5).

$$PSNR = 10\log_{10}(255^2/MSE) \tag{1}$$

$$MSE = (1/MN)\Sigma_{i=1}^{M}\Sigma_{j=1}^{N}[O(m,n] - R(m,n)]^2 \tag{2}$$

$$RMSE = [(1/MN)\Sigma_{i=1}^{M}\Sigma_{j=1}^{N}[O(m,n] - R(m,n)]^2]^{1/2} \tag{3}$$

$$IEF = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}(N(m,n) - O(m,n))^2}{\sum_{i=1}^{M}\sum_{j=1}^{N}(D(m,n) - O(m,n))^2} \tag{4}$$

$$SSIM = \frac{(2\mu_O\mu_R + C_1)(2\sigma_{OR} + C_2)}{(\mu_O^2 + \mu_R^2 + C_1)(\sigma_O^2 + \sigma_R^2 + C_2)} \tag{5}$$

Where, O is the original image; R, the restored image; D, de-noised image; μ_O and μ_R are the averages of O and R respectively; σ_O^2 and σ_R^2 are variances of O and R respectively; σ_{OR} is the correlation coefficient between O and R; C_1 and C_2 are small constants for stabilize the computation; $C_1 = (k_1+L)^2$ $C_2 = (k_2+L)^2$ $k_1 = 0.01$ and $k_2 = 0.03$ by default; L=255.

4.   RESULTS AND DISCUSSION

The performance of the proposed ENAMF algorithm for various images at different noise levels varying from 10% to 90% is tested by using MATLAB. Results of both gray scale and color standard images are shown in the Figures 2, 11 and 12 respectively. Figure 2 (a) is the *Lena.jpg* image corrupted with 30% of salt and pepper noise. The same image is restored with VMF, SMF, ROAMF, DBA and proposed filter are shown in Figure 2(b), 2(c), 2(d), 2(e) and 2(f) respectively. The same image corrupted with 90% of salt and pepper noise and restored with VMF, SMF, ROAMF, DBA and proposed filter are shown in Figure 2(g), 2(h), 2(i), 2(j), 2(k) and 2(l) respectively. Similarly, The color image *Rose.jpg* with both 20% and 90% of noise density, *Pepper.jpg* image with both 30% and 90% noise densities are shown in Figure 11 and 12 respectively. These images were restored with VSM, SMF, ROAMF, DBA and Proposed Filter are shown in Figure 11 (a) through 11(l) and Figure 12(a) through 12(l) respectively.
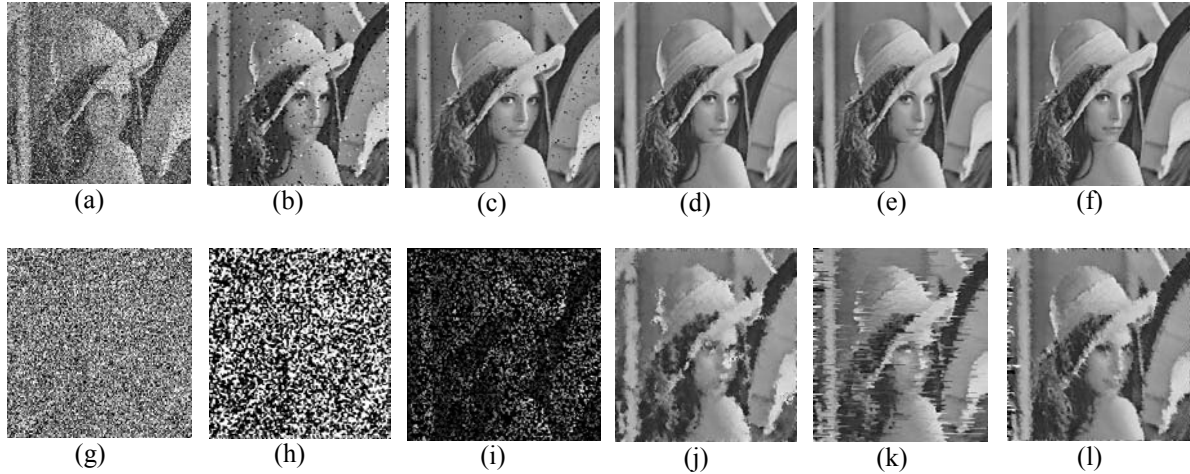
Figure 2. (a) Gray-Scale Lena Image with 30% Noise Density and same image restored with, (b) VMF, (c) SMF, (d) ROAMF, (e) DBA, (f) Proposed ENAMF Algorithm, (g) Gray-Scale Lena Image with 90% Noise Density and same image restored with, (h) VMF, (i) SMF, (j) ROAMF, (k) DBA, (l) Proposed ENAMF Algorithm

Tables 1 through 8 show the quantitative measures and their corresponding graphs are shown in the Figures 3 through 10. The variations of PSNR and SSIM metrics of the proposed ENAMF algorithm in graphs given in Figures 3, 5, 6, 8 and 10 clearly show the effectiveness of our proposed algorithm.

Table 1. Comparison of PSNR values of different algorithms for *Lena.jpg* image at different noise densities (%)

Noise Density	VMF	SMF	ROAMF	DBA	ENAMF
10	40.8980	39.7968	45.3268	45.3338	45.3798
20	40.9273	39.7924	44.4665	44.4737	44.5050
30	40.8734	39.8156	43.6524	43.6984	43.7899
40	40.5356	39.8474	42.9280	42.9469	42.9961
50	40.0220	39.9571	42.2795	42.3702	42.4495
60	39.3077	40.1553	41.7460	41.7581	41.9359
70	38.7015	40.5394	41.2068	41.3837	41.4766
80	38.2770	41.1648	40.6099	40.6636	40.6840
90	37.921	42.407	39.8347	39.9260	39.996

Table 2. Comparison of MSE values of different algorithms for *Lena.jpg* image at different noise densities (%)

Noise Density	VMF	SMF	ROAMF	DBA	ENAMF
10	5.2878	6.814	1.9072	1.9086	1.9028
20	5.2523	6.8209	2.3357	2.3343	2.3332
30	5.3179	6.7846	2.8044	2.8027	2.8004
40	5.748	6.7351	3.3134	3.2991	3.2879
50	6.4696	6.5671	3.8470	3.8353	3.8238
60	7.6262	6.2741	4.3499	4.3468	4.3406
70	8.7685	5.7431	4.9549	4.9412	4.9293
80	9.112	4.9728	5.6506	5.5811	5.5265
90	10.4943	3.7355	6.9012	6.7996	6.5360

Table 3. Comparison of SSIM values of different algorithms for *Lena.jpg* image at different noise densities (%)

Noise Density	VMF	SMF	ROAMF	DBA	ENAMF
10	0.74173	0.39827	0.97845	0.97811	0.97803
20	0.66694	0.42281	0.96821	0.96828	0.96839
30	0.41703	0.39674	0.94815	0.9482	0.94825
40	0.21677	0.29722	0.92711	0.92582	0.92517
50	0.10957	0.17839	0.89572	0.89173	0.89961
60	0.05919	0.11192	0.85497	0.8450	0.86294
70	0.03914	0.07262	0.79572	0.77428	0.81345
80	0.02754	0.04576	0.71089	0.65870	0.74670
90	0.01080	0.02420	0.54784	0.43148	0.57714

Table 4. Comparison of PSNR values of different algorithms for *Rose.jpg* Color image at different noise densities (%)

Noise Density	VMF	SMF	ROAMF	DBA	ENAMF
10	39.3117	37.8419	44.7613	43.7425	44.0239
20	39.3372	37.8426	43.4063	42.8248	42.9395
30	39.2809	37.8595	42.3513	41.9346	41.9747
40	38.9789	37.9032	41.4339	41.1126	41.1603
50	38.4380	37.9887	40.7589	40.5174	40.5077
60	37.6908	38.2014	39.8464	39.8009	39.9246
70	36.9748	38.5355	39.2082	39.2183	39.2974
80	36.3067	39.2071	38.6191	38.6576	38.6903
90	35.7648	40.5428	37.6580	37.6819	37.9705

Table 5. Comparison of IEF values of different algorithms for *Rose.jpg* color image at different noise densities (%)

Noise Density	VMF	SMF	ROAMF	DBA	ENAMF
10	64.9416	8.6023	1847.830	1483.303	1373.031
20	37.7106	9.0624	728.2537	613.4074	514.8036
30	14.2048	4.3171	408.0800	373.1223	245.8448
40	5.8017	7.6858	207.5704	205.0594	144.3070
50	2.7089	5.8298	136.8841	137.1217	91.60810
60	1.5172	3.9963	91.14450	75.89670	53.55280
70	0.98159	2.7281	56.45650	40.38440	34.05000
80	0.70612	1.8728	33.92840	23.03540	23.12300
90	0.55837	1.3293	12.17640	8.32540	9.3831

Table 6. Comparison of SSIM values of different algorithms for *Rose.jpg* color image at different noise densities (%)

Noise Density	VMF	SMF	ROAMF	DBA	ENAMF
10	0.88794	0.6534	0.98781	0.98835	0.99017
20	0.82869	0.66406	0.98205	0.98273	0.98434
30	0.65872	0.65151	0.97224	0.97375	0.97415
40	0.41997	0.60971	0.96032	0.96308	0.96739
50	0.21974	0.53295	0.94146	0.94259	0.94962
60	0.10236	0.46176	0.92189	0.91477	0.92498
70	0.04596	0.40144	0.88126	0.86988	0.89865
80	0.02451	0.35039	0.81799	0.79103	0.84842
90	0.01339	0.3001	0.66172	0.6149	0.72576

Table 7. Comparison of IEF values of different algorithms for *Pepper.jpg* color image at different noise densities

Noise Densit	VMF	SMF	ROAMF	DBA	ENAMF
10	48.0584	12.9805	853.229	976.0407	861.697
20	32.3596	13.3792	456.1295	470.8866	405.911
30	14.3803	12.7267	264.8490	264.6491	218.676
40	6.6947	10.0648	183.279	180.8945	139.488
50	3.4134	6.9723	125.8887	116.1001	93.0647
60	2.0618	4.5126	87.7070	77.8606	63.6503
70	1.3939	2.9145	60.8757	50.4619	44.0758
80	1.0705	1.9490	37.2095	27.9222	28.5607
90	0.9069	1.3489	19.6878	12.7480	14.4200

Table 8. Comparison of SSIM values of different algorithms for *Pepper.jpg* color image at different noise densities

| Noise Densi	VMF	SMF	ROAMF	DBA	ENAMF
10	0.83604	0.56461	0.99021	0.98831	0.98888
20	0.75807	0.57797	0.97218	0.9694	0.96983
30	0.54254	0.55053	0.97041	0.96813	0.96998
40	0.31375	0.45304	0.95074	0.95103	0.95158
50	0.16763	0.33378	0.93292	0.92789	0.93068
60	0.09423	0.23578	0.89825	0.89558	0.90821
70	0.05373	0.17426	0.85929	0.84087	0.87877
80	0.03074	0.12936	0.78512	0.75493	0.81784
90	0.01954	0.03906	0.64322	0.57273	0.68982
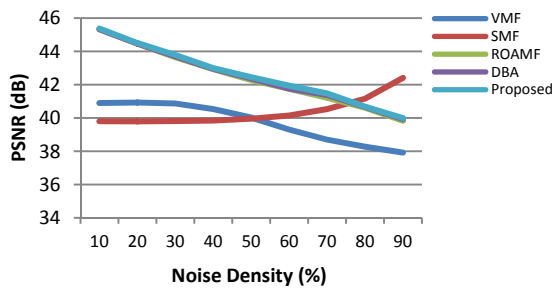
Figure 3. Noise Density versus PSNR for Gray-Scale Lena Imageat different noise densities
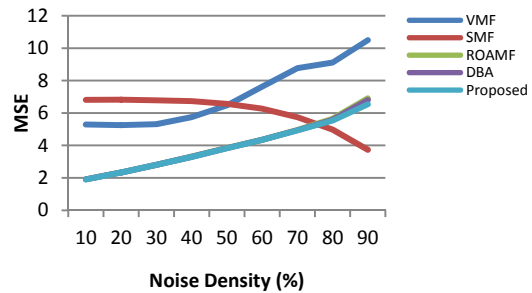

Figure 4. Noise Density versus MSE for Gray-Scale Lena Image at different noise densities
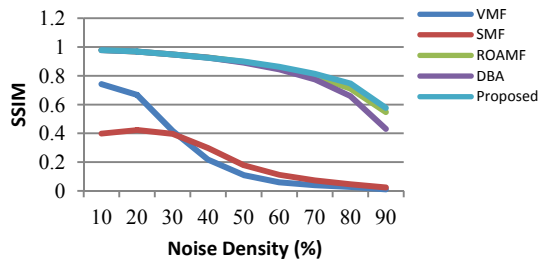

Figure 5. Noise Density versus SSIM for Gray-Scale Lena Image at different noise densities
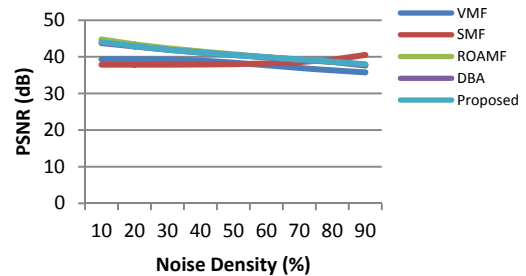

Figure 6. Noise Density versus PSNR for Rose Image at different noise densities
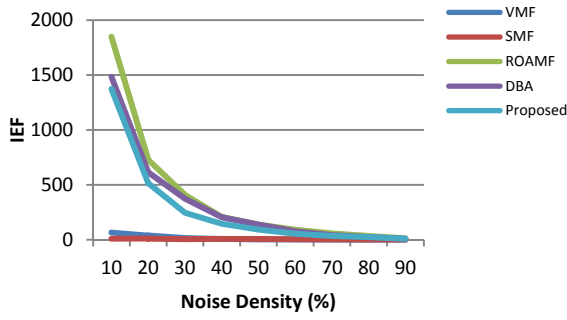
Figure 7. Noise Density versus IEF for color Rose Image at different noise densities
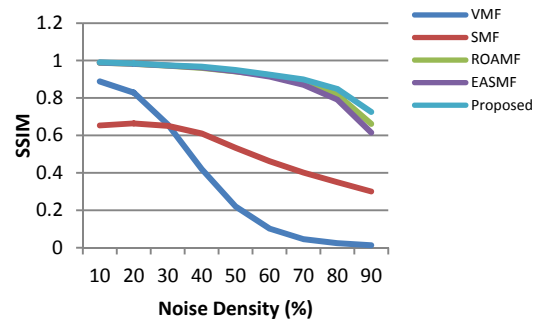

Figure 8. Noise Density versus SSIM for color Rose Image at different noise densities
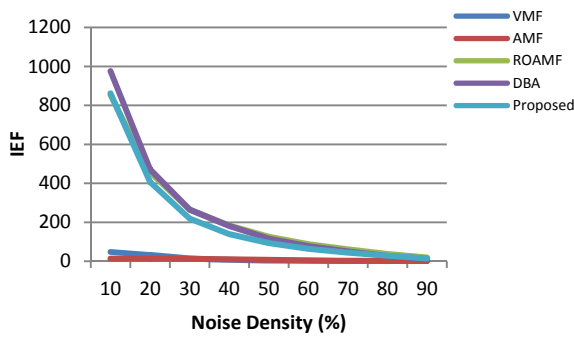

Figure 9. Noise Density versus IEF for Pepper Image at different noise densities
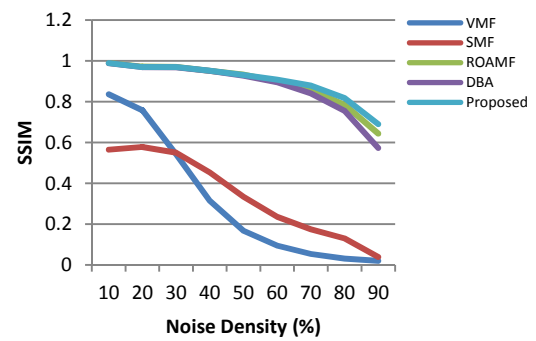

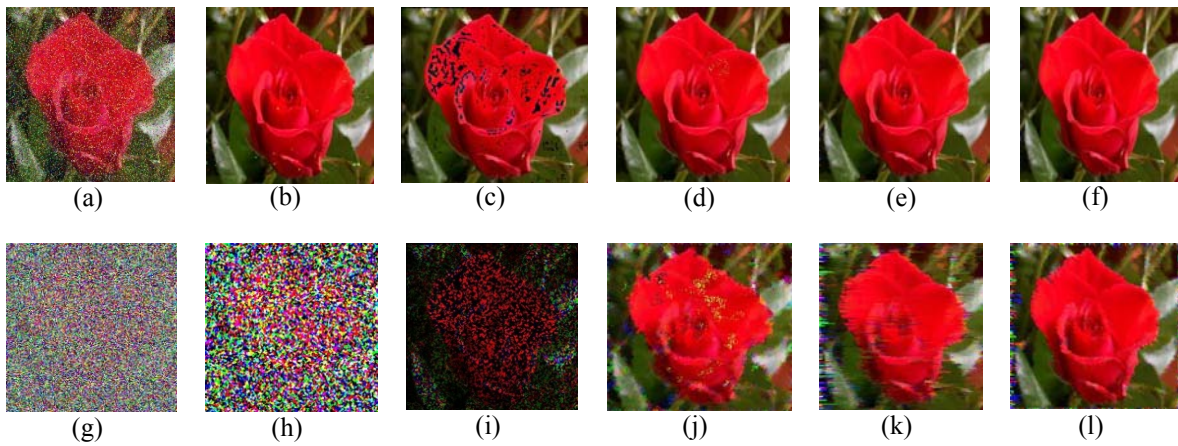Figure 10. Noise Density versus SSIM for Pepper Image at different noise densities

Figure 11. (a) Rose Image with 20% Noise Density and same image restored with (b) VMF, (c) SMF, (d) ROAMF, (e) DBA, (f) Proposed ENAMF Algorithm (g) Rose Image with 90% Noise Density and same image restored with (h) VMF, (i) SMF, (j) ROAMF, (k) DBA, (l) Proposed ENAMF Algorithm
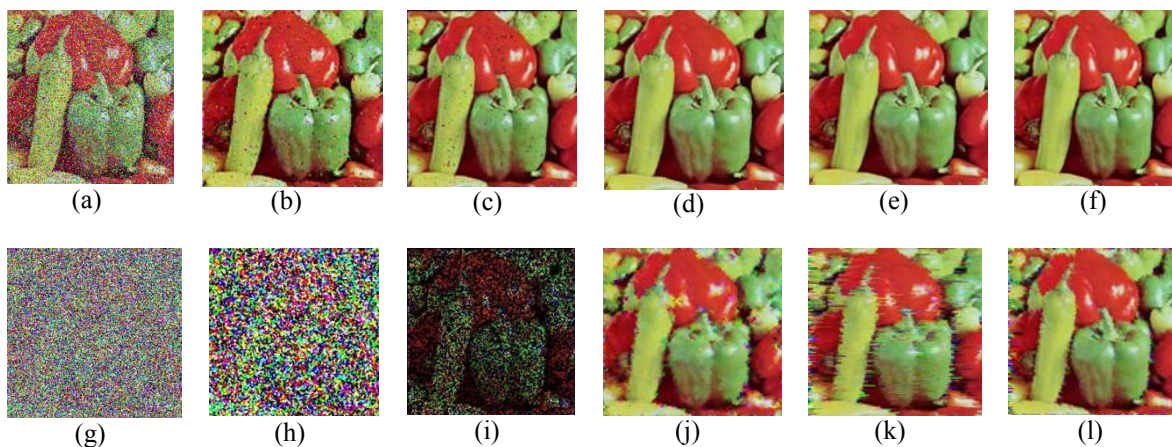
Figure 12. (a) Pepper Image with 30% Noise Density and same image restored with (b) VMF, (c) SMF, (d) ROAMF, (e) DBA, (f) Proposed ENAMF Algorithm, (g) Pepper Image with 90% Noise Density and same image restored with (h) VMF, (i) SMF,(j) ROAMF, (k) DBA, (l) Proposed ENAMF Algorithm

The Table 1 and Table 4 clearly show the PSNR values of the filtered images from different algorithms, which realize the preservation of image quality of our proposed ENAMF. Table 2 shows the MSE of the filtered images from different algorithms, which realize our proposed algorithm has the minimum error rate when compared with other filtering results. The SSIM values of the tested images are shown in Tables 3, 6 and 8. From these tables and their corresponding graphs, Figure 5, 8 and 10 shows the betterment of our proposed filter when compared with other non-linear filters. The IMF values of the proposed filter resembles with DBA, which are given in Table 7 and 9 respectively. The streaking effect such as horizontal and diagonal streaks that normally occur in DBAs are rectified by correct selection of the neighborhood pixels in our proposed filtering algorithm which in turn gives a better visual perception as shown in figures 2(l), 11(l) and 12(l).

5.   CONCLUSION AND FUTURE DIRECTION

In this paper, a new effective noise adaptive median filter is proposed which gives better performance in comparison with VMF, SMF, ROAMF and DBA in terms of PSNR, MSE, RMSE, SSIM and IEF metrics. The proposed algorithm is faster than ROAMF since it uses a small and fixed window of size 3×3. In addition, it affects a smooth transition between the pixel values by utilizing the correlation between neighboring processed pixels while preserving edge details thus leading to better edge preservation. The proposed filter is tested from low to high noise densities on different grayscale images and color images that yield recognizable and patches free restoration. The significant difference in PSNR, SSIM and visual perception with other competitive filters quantifies a dominance of the proposed filter. In future, fuzzy logic based adaptive switching median filter will play the dominant role in digital image restoration.

REFERENCES

[1]   Rafael C. Gonzalez and Richard E. Wood. *Digital Image Processing*. 3rd Edition, Prentice-Hall, 2009.
[2]   Abdul Saleem S, and Abdul Razak T. Survey on Color Image Enhancement Techniques using Spatial Filtering. *International Journal of Computer Applications (IJCA)*. 2014; 94(9): 39-45.
[3]   Manglem Sigh Kh., Bora Prabin K., and Birendra Singh. S. Vector Median Filter for Removal of Impulse Noise from Color Images. *IU-Journal of Electrical and Electronics Engineering*. 2004; 4(1): 1063-1072.
[4]   Hwang H. and Hadded R.A. Adaptive Median Filter: New algorithms and results. *IEEE Transactions. Image Processing*. 1995; 4(4): 499–502.
[5]   Browning D.R.K. The Weighted Median Filter. *Communications of the ACM*. 1984; 27(8): 807-818.
[6]   Zhou Wang and David Zhang. Progressive Switching Median Filter for Removal of Impulse noise from Highly Corrupted Images. *IEEE Transaction s on Circuit and Systems-II, Anolog and Digital Signal Processing*. 1999; 46(1).
[7]   Z. Wang, A.C. Bovik, H.R. Sheikh and E.P. Simoncelli. Image Quality Assesment: From error measurement to structural similarity. *IEEE Transactions on Image Processing*. 2004; 13(1).
[8]   Kwame Osei Boating, Benjamin Weyori Asubam and David Sanka Laar. Improving the Effective ness of the Median Filter. *International Journal of Electronic and Communication Engineering*. 2012; ISSN 0974-2166; 5(1): 85-97.

[9]   Akkoul S., Ledee. Roger, Leconge. R, Harba R. A New Adaptive Switching Median Filter. *Signal Processing Letters. IEEE*. 2010; 17(6).
[10] Srinivasan K.S. and Ebenezer D. A new fast and efficient decision based algorithm for removal of high density impulse noise. *IEEE signal processing*. 2007; 14(3):189-192.
[11] Nair Madhu S., Revathy K. and Tatavarti Rao. "Removal of Salt and Pepper Noise in Images: A new Decision-Based Algorithm", *Proceeding of International Multi Conference of Engineers and Computer Scientists*. 2008; 1: 19-21: IMECS.
[12] Aiswarya K., Jayaraj V., Ebenezer D. A New and Efficient Algorithm for the Removal of High density Salt and Pepper Noise in Images and Videos. *IEEE*. 2010; 978-0-7695-3941.

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