# An Effective Adaptive Nonlinear Filter for Removing High Density Impulse Noises in Gray-Scale Images

S. Abdul Saleem #1 , Dr. T. Abdul Razak #2

[1] Research Scholar, Bharathidasan University, Tiruchirappalli, Tamil Nadu, India

[1] saleemnts@gmail.com

[2] Associate Professor of Computer Science , Jamal Mohamed College, Tiruchirappalli, Tamil Nadu, India

[2] abdul64@yahoo.com

**Abstract - Digital images are often distorted by Impulse noise during the process of analog-to-digital conversion, transmission and storage in the physical medias. This type of error certainly changes the properties of some of the pixels while some of the other pixels remain unchanged. In order to remove impulse noise and enhance the distorted image quality, we have tested the number of nonlinear filters and their limitations and we have proposed a new efficient adaptive nonlinear filtering algorithm. This method removes or effectively suppresses the impulse noises in the gray-scale images while preserving the image edges information and enhancing the image quality. The proposed method is a spatial domain approach and uses the 3×3 kernel window to filter the signal based on the correct selection of neighbourhood values to obtain the median per window. The method chosen in this work is based on a functional level 2n +1 window that makes the selection of the normal median easier, since the number of elements in the window is odd. The median so obtained is set as the efficient value for filtering. Suppose the median is an impulse, a more representative value is pursued from the neighbourhood values and used as the median value. The performance of the proposed efficient adaptive nonlinear filter has been evaluated using MATLAB, simulations on gray-scale digital images that have been subjected to high density of corruption with impulse noise as high as 90 %. The results reveal the effectiveness of our proposed algorithm when compared with existing vector, standard and adaptive median filtering algorithms.**

**Keywords -** Frequency domain, spatial domain, impulse noise, median filters, image restoration, image parameters

## I. Introduction

Image Processing is one of the important and fast emerging fields in the area of computer science and engineering. The growth of this field has been improved by the technological developments in digital computing, computer processors, digital data processing and mass storage devices. All fields which were operating on the analog signals are now gradually converting into the digital systems for their ease of use, reliability and flexibility. Image processing is very useful and has been extensively applied in the area of medicine, film and video production, photography, remote sensing, desktop publishing, military target analysis, and manufacturing automation and control. Most of the real time applications usually require bright and clear images or pictures, hence distorted or degraded images need to be processed to enhance easy identification and further works on the image. Image processing techniques such as image enhancement, image restoration, image filtering and object recognition are used to process the image depending on the type of interference that has caused the degradation [1].

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 analog-to-digital conversion, transmission through communication media and storage in the physical medias. Several filtering techniques have been developed over the past decades for various applications. The type of noise factor and intensity of the noise that has degraded the image is also taken in to consideration before the filter is developed and used.

The filtering techniques can be categorized 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 but, the frequency domain filtering techniques have to do with modifying the Fourier transform of the interested image. The spatial domain filtering is further classified into linear 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[1][2].

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 filter method cannot achieve the desired result[2].

Vector Median Filter(VMF) is an extension of Scalar Median Filter which suppresses the noise in the geophysical data represented by multi-dimensional array. The VMF algorithm is also applied on the digital images for filtering the impulse noises up to 50% of noise level. The Standard Median Filter (SMF) is a simple rank selection filter that attempts to remove 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[3][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 neighbourhood of a particular signal [5].

The Progressive Switching Median Filter 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[6]. 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.

In this paper, we propose a spatial domain method using the overlapping kernel window to filter the image based on the selection of neighbouring 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 quantitative measures such as Peak Signal to Noise Ratio(PSNR), Mean Square Error(MSE) and Structural Similarity Index Metric (SSIM) show the significant improvement when compare with other adaptive median filters [7].

This paper is organized as follows: Section II discusses the noises that normally affect the digital images during communication. Section III discusses impulse noise removal technique using adaptive median and some of its derivative filters and their limitations. Section IV presents the proposed effective adaptive median filtering technique and its implementation. The comparison of proposed filter with other non-linear filters by using quantitative metrics is given in Section V and finally the paper is concluded with future direction in Section VI.

## II. NOISE MODEL

Noises in the digital images are modelled as three standard categories, they are additive noises, multiplicative noises and random impulse noises[3]. Most of the digital images are normally corrupted by impulse noise during communication. The impulse noise is called as 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 $P1\neq P2$. In this paper we are merely considering random valued impulse noise with $P1\neq P2$.

## III. 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) 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 50% 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][12].

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][10].

Decision Based Algorithm(DBA) was 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 [11][12].

## IV. PROPOSED EFFECTIVE ADAPTIVE NON LINEAR FILTER

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 efficient adaptive nonlinear 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.

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 DBAs are rectified in the proposed algorithm by restoring the correct pixel values depending on the number of noisy pixels in the kernel window.

The explanatory steps of the proposed algorithm for the gray scale images are given as follows

The two dedicated steps of the filter are:

Step 1: involves the adaptive detection of impulsive locations in gray-scale image.

Step 2: involves the correction of the detected impulsive pixels with an appropriate value from an acceptable neighborhood pixels.

### A. *Algorithm*

Input: Gray Scale Noisy Image Img

Output: Filtered Image b

Step 1: Set the kernel window size 3×3, noisy image ‘a’ and restored image ‘b’

Step 2: Read the pixels from the sliding window on the noisy image and store it in S

Step 3: Compute $S_{min}$, $S_{max}$ $S_{med}$ and $N_p$

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 considering as corrupted pixel and replace b(i,j) by $S_{med}$. Otherwise go to step 6.

Step 6: If $N_p$>=5 and b(i,j-1)=0, then it is consider as corrupted pixel and replace b(i,j) by $S_{min}$. If $N_p$ >= 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 256×256 jpeg gray scale image.

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 gives best possible restoration even in highly corrupted environment up to 90%. The horizontal and diagonal streaks are less when compare 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 adaptive nonlinear filter from other adaptive filters.

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

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

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

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

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

$C_1 = (k_1+L)^2$ $\quad$ $C_2 = (k_2+L)^2$

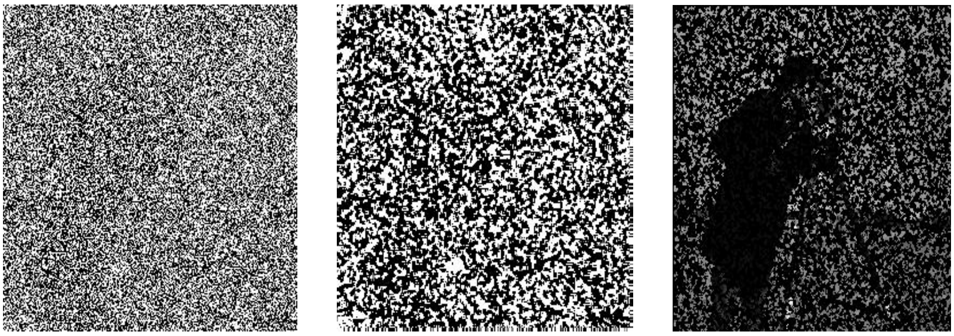
Where, O is the original image; R, the restored image; D, denoised image; $\mu_O$ and $\mu_R$ are the averages of O and R respectively; $\sigma_O^2$ and $\sigma_R^2$ are variances of O and R respectively; $\sigma_{OR}$ is the correlation coefficient between O and R; $C_1$ and $C_2$ are small constants for stabilize the computation; $k_1$=0.01 and $k_2$=0.03 by default; L=255.

## V. COMPARISON OF OTHER ADAPTIVE MEDIAN FILTERS WITH PROPOSED FILTER

(a) (b) (c) (d)

(e) (f) (g)

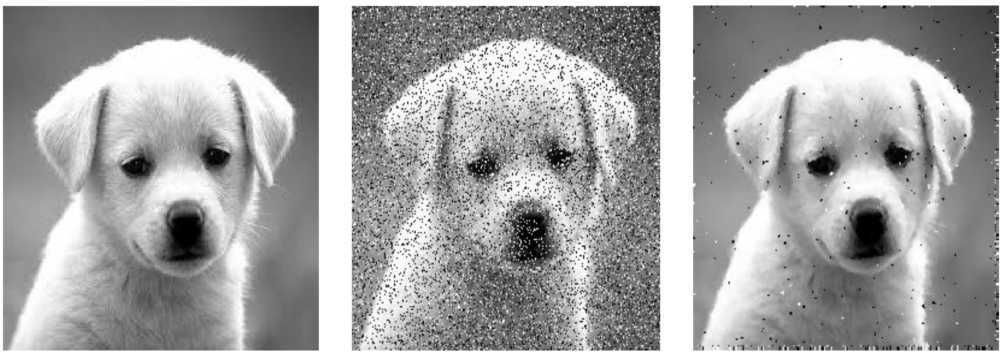
Fig. 1: (a) Noise Free Cameraman Image, (b) Cameraman Image(.jpg) with 20% Noise Density and same image restored with (c) VMF, (d) SMF,(e)ROAMF,(f) DBA, and (g) Proposed Algorithm



(h) (i) (j)

(k) (l) (m)

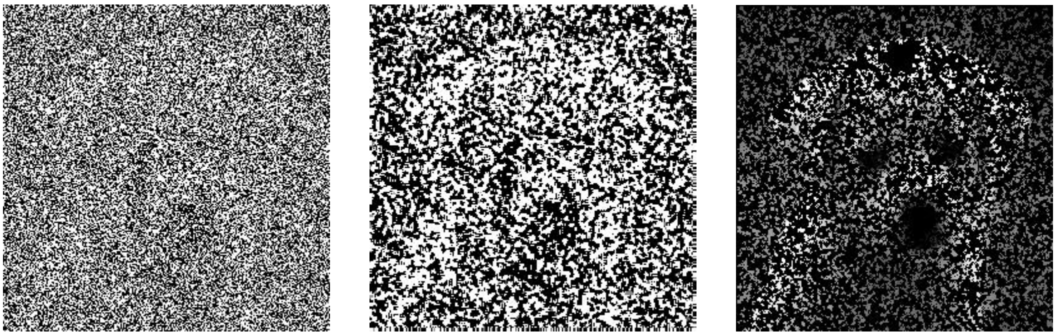
Fig. 2: (h) Cameraman Image with 90% Noise Density and same image restored with (i) VMF,(j) SMF, (k) ROAMF,(l) DBA and (m) Proposed Algorithm



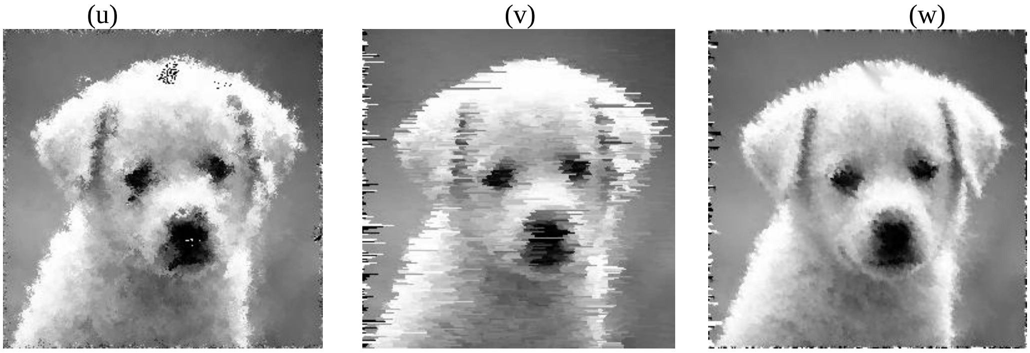
(n) (o) (p)

(q) (r) (s) (t)

Fig. 3: (n) Noise Free Puppy Image, (o) Puppy Image with 20% Noise Density and same image restored with (p) VMF, (q) SMF, (r)ROAMF,(s) DBA and (t) Proposed Algorithm



(u) (v) (w)



(x) (y) (z)

Fig. 4: (u) Puppy Image with 90% Noise Density and same image restored with (v) VMF,(w) SMF,(x)ROAMF,(y) DBA and (z) Proposed Algorithm

TABLE I. Comparison of PSNR values of Different Algorithms for Cameraman image at different Noise Densities (%)

| Noise Density (%) | VMF | SMF | ROAMF | DBA | PF |
|---|---|---|---|---|---|
| 10 | 41.3800 | 40.2463 | 44.9947 | 44.9030 | 44.9945 |
| 20 | 41.4129 | 40.2400 | 44.2588 | 44.2550 | 44.4568 |
| 30 | 41.3450 | 40.2569 | 43.5846 | 43.5830 | 43.9851 |
| 40 | 40.8561 | 40.2822 | 42.9094 | 42.6366 | 43.0099 |
| 50 | 40.2362 | 40.3867 | 42.4529 | 42.4466 | 42.8561 |
| 60 | 39.3975 | 40.6157 | 41.8696 | 41.6777 | 41.9926 |
| 70 | 38.7233 | 40.9351 | 41.4035 | 41.4567 | 41.7242 |
| 80 | 38.2499 | 41.5563 | 40.9877 | 40.9962 | 41.2276 |
| 90 | 37.8973 | 42.8845 | 40.4112 | 40.4113 | 40.7506 |

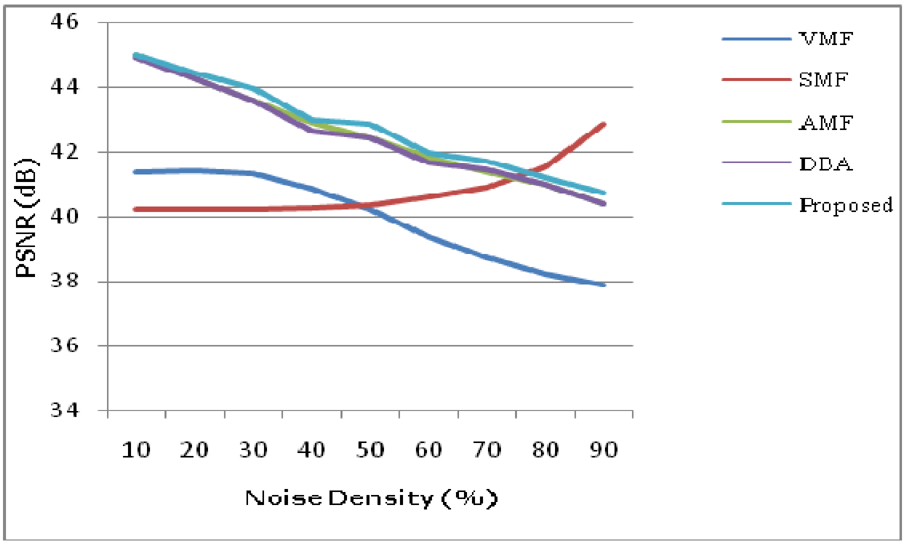



Fig. 5. Noise Density versus PSNR for Cameraman Image

TABLE II. Comparison of MSE values of Different Algorithms for Cameraman image at different Noise Densities (%)

| Noise Density (%) | VMF | SMF | ROAMF | DBA | PF |
|---|---|---|---|---|---|
| 10 | 4.7323 | 6.1439 | 2.0588 | 2.1040 | 2.0575 |
| 20 | 4.6912 | 6.1530 | 2.4390 | 2.4411 | 2.4127 |
| 30 | 4.7707 | 6.1290 | 2.8485 | 2.8496 | 2.7812 |
| 40 | 5.3391 | 6.0935 | 3.3277 | 3.3069 | 3.2455 |
| 50 | 6.1582 | 5.9485 | 3.6965 | 3.7019 | 3.6756 |
| 60 | 7.4701 | 5.6430 | 4.2279 | 4.2200 | 4.1739 |
| 70 | 8.7246 | 5.2429 | 4.7068 | 4.6496 | 4.5936 |
| 80 | 9.7295 | 4.5441 | 5.1798 | 5.1697 | 5.0619 |
| 90 | 10.5523 | 3.3468 | 5.9150 | 5.9149 | 5.4513 |

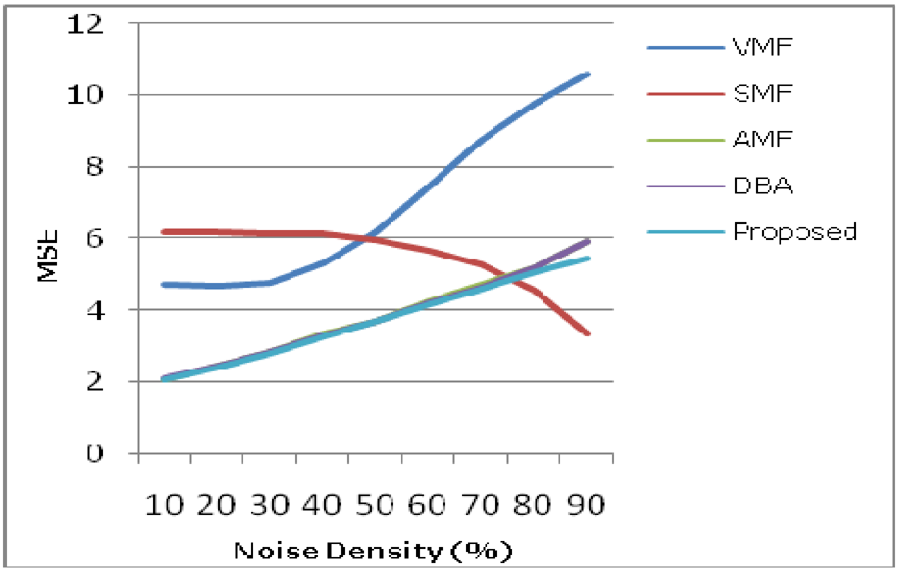



Fig. 6. Noise Density versus MSE for Cameraman Image

TABLE III. Comparison of RMSE values of Different Algorithms for Cameraman image at different Noise Densities (%)

| Noise Density (%) | VMF | SMF | ROAMF | DBA | PF |
|---|---|---|---|---|---|
| 10 | 2.1754 | 2.4787 | 1.4349 | 1.4505 | 1.4344 |
| 20 | 2.1659 | 2.4805 | 1.5617 | 1.5624 | 1.5533 |
| 30 | 2.1842 | 2.4757 | 1.6878 | 1.6881 | 1.6677 |
| 40 | 2.3107 | 2.4685 | 1.8242 | 1.8185 | 1.8015 |
| 50 | 2.4816 | 2.4390 | 1.9226 | 1.9240 | 1.9172 |
| 60 | 2.7332 | 2.3755 | 2.0562 | 2.0543 | 2.0430 |
| 70 | 2.9537 | 2.2897 | 2.1695 | 2.1563 | 2.1433 |
| 80 | 3.1192 | 2.1317 | 2.2759 | 2.2737 | 2.2499 |
| 90 | 3.2484 | 1.8294 | 2.4321 | 2.4321 | 2.3348 |

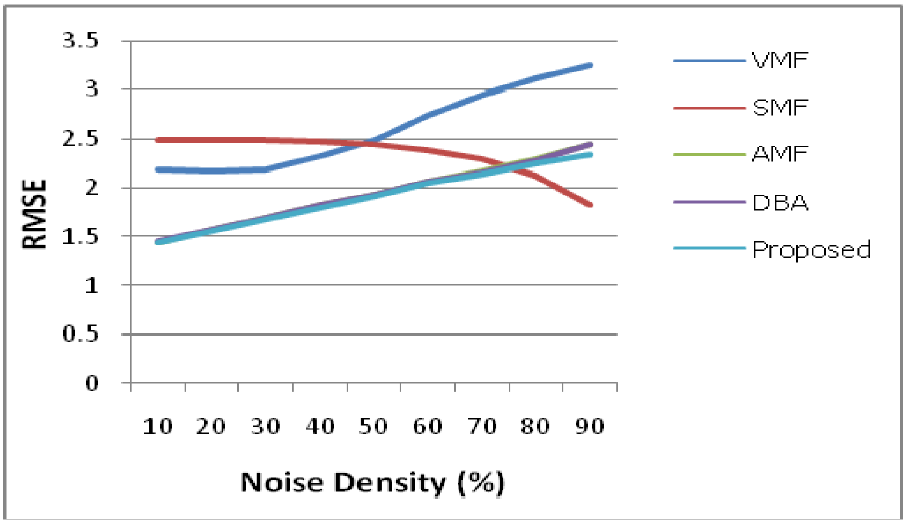



Fig. 7. Noise Density versus RMSE for Cameraman Image

TABLE IV. Comparison of SSIM values of Different Algorithms for Cameraman image at different Noise Densities (%)

| Noise Density (%) | VMF | SMF | ROAMF | DBA | PF |
|---|---|---|---|---|---|
| 10 | 0.75204 | 0.14732 | 0.97167 | 0.96189 | 0.98249 |
| 20 | 0.67099 | 0.16168 | 0.96097 | 0.95796 | 0.96003 |
| 30 | 0.42465 | 0.1686 | 0.94232 | 0.94215 | 0.94243 |
| 40 | 0.20165 | 0.16664 | 0.92207 | 0.92249 | 0.92338 |
| 50 | 0.10674 | 0.14489 | 0.88637 | 0.88753 | 0.88511 |
| 60 | 0.05627 | 0.11826 | 0.84140 | 0.84477 | 0.84940 |
| 70 | 0.03152 | 0.09282 | 0.79147 | 0.79145 | 0.80485 |
| 80 | 0.01991 | 0.06668 | 0.71486 | 0.71522 | 0.73885 |
| 90 | 0.01229 | 0.04677 | 0.58260 | 0.56480 | 0.64823 |

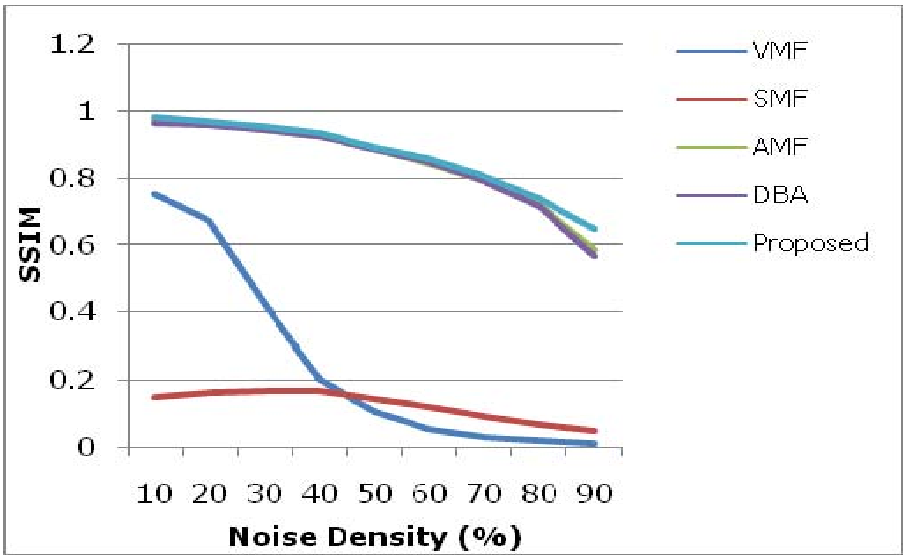



Fig. 8. Noise Density versus SSIM for Cameraman Image

TABLE V. Comparison of PSNR values of Different Algorithms for Puppy image at different Noise Densities (%)

| Noise Density (%) | VMF | SMF | ROAMF | DBA | PF |
|---|---|---|---|---|---|
| 10 | 41.463 | 40.2215 | 46.2398 | 46.1819 | 46.2578 |
| 20 | 41.3874 | 40.2333 | 45.3794 | 45.3712 | 45.3952 |
| 30 | 41.1031 | 40.2343 | 44.3836 | 44.4015 | 44.4648 |
| 40 | 40.6415 | 40.2804 | 43.6947 | 43.0113 | 43.6364 |
| 50 | 40.0593 | 40.3973 | 43.1207 | 43.1125 | 43.2349 |
| 60 | 39.3522 | 40.5991 | 42.4504 | 42.4479 | 42.4629 |
| 70 | 38.7126 | 40.8972 | 41.8546 | 41.8364 | 41.8613 |
| 80 | 38.2961 | 41.5416 | 41.1940 | 41.0716 | 41.2140 |
| 90 | 38.0276 | 42.9557 | 40.3715 | 40.0596 | 39.9878 |

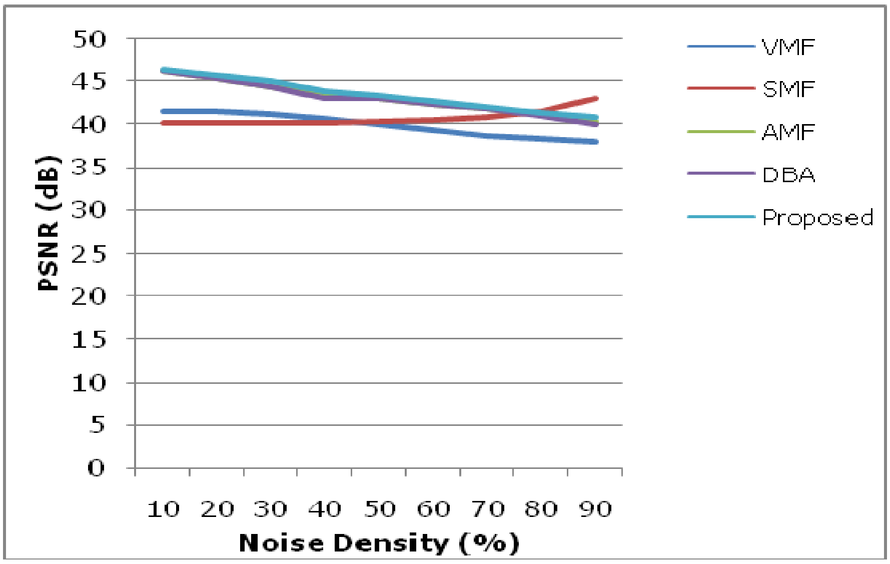



Fig. 9. Noise Density versus PSNR for Puppy Image

TABLE VI. Comparison of Time values of Different Algorithms for Puppy image at different Noise Densities (%)

| Noise Density (%) | VMF | SMF | ROAMF | DBA | PF |
|---|---|---|---|---|---|
| 10 | 1.4767 | 1.0173 | 2.3887 | 1.3342 | 1.2188 |
| 20 | 1.5994 | 1.1679 | 2.5427 | 1.6911 | 1.5058 |
| 30 | 1.5327 | 1.0264 | 2.2723 | 1.8434 | 1.5252 |
| 40 | 1.4911 | 1.0162 | 2.2235 | 1.9493 | 1.6444 |
| 50 | 1.4888 | 1.0150 | 2.3541 | 2.0347 | 1.7683 |
| 60 | 1.4668 | 1.0173 | 2.5833 | 2.1366 | 1.7953 |
| 70 | 1.4453 | 1.0181 | 2.8112 | 2.3393 | 1.8838 |
| 80 | 1.4205 | 1.0160 | 4.0296 | 2.4424 | 1.9815 |
| 90 | 1.3827 | 1.0142 | 9.1081 | 2.5394 | 2.1088 |

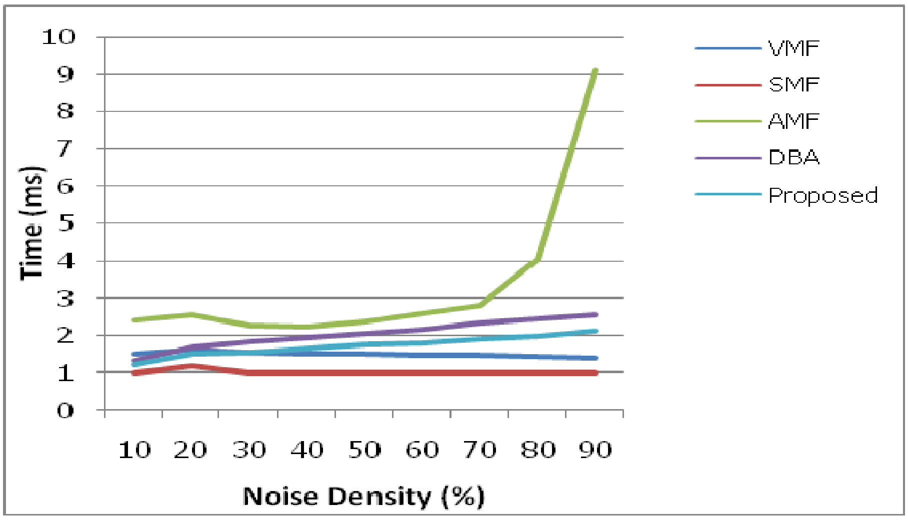



Fig. 10. Noise Density versus TIME(ms) for Puppy Image

TABLE VII. Comparison of SSIM values of Different Algorithms for Puppy image at different Noise Densities (%)

| Noise Density (%) | VMF | SMF | ROAMF | DBA | PF |
|---|---|---|---|---|---|
| 10 | 0.83184 | 0.34021 | 0.97510 | 0.97511 | 0.97878 |
| 20 | 0.73020 | 0.34261 | 0.96427 | 0.96762 | 0.96656 |
| 30 | 0.46672 | 0.31569 | 0.94887 | 0.95475 | 0.95156 |
| 40 | 0.21243 | 0.23175 | 0.92785 | 0.92495 | 0.92893 |
| 50 | 0.10108 | 0.14110 | 0.90401 | 0.90934 | 0.93357 |
| 60 | 0.04818 | 0.07515 | 0.86347 | 0.87127 | 0.87325 |
| 70 | 0.02945 | 0.04347 | 0.82310 | 0.82023 | 0.83847 |
| 80 | 0.01882 | 0.02699 | 0.75021 | 0.73407 | 0.77530 |
| 90 | 0.00776 | 0.01437 | 0.58832 | 0.54357 | 0.67769 |

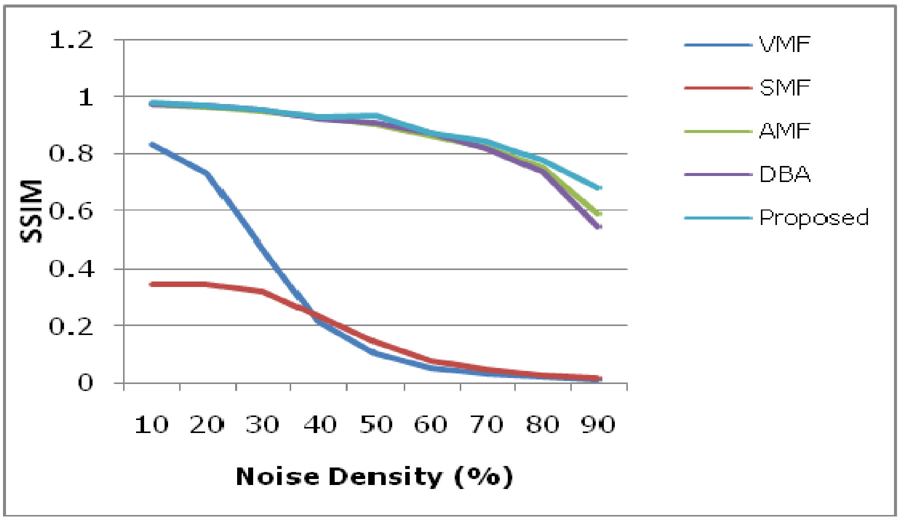



Fig. 11. Noise Density versus SSIM for Puppy Image

The performance of the proposed algorithm for various images at different noise levels varying from 10% to 90% is studied. Results of two images are shown in the figures 1,2 3 and 4. Fig. 1 (a) is the uncorrupted Cameraman image with M×N size, Fig 1 (b) is the Cameraman image corrupted with 20% of salt and pepper noise. The same image is restored with VMF, SMF, ROAMF, DBA and Proposed filter are shown in Fig 1(c), 1(d), 1(e), 1(f) and 1(g) respectively. Similarly, Cameraman image with 90% noise density, Puppy image with both 20% and 90% noise densities are shown in Fig. 2,3 and 4, the same corrupted image restored with VSM,SMF,ROAMF,DBA and Proposed Filter are shown in (h) through (z) images. Table I to VII display the quantitative measures and their corresponding graphs are shown from figures 5 through 11.

The variations of PSNR,MSE,RMSE,TIME and SSIM metrics of the proposed algorithm in graphs Fig 5 through 11 clearly show the effectiveness of our proposed algorithm.

## VI. Conclusion

In this paper, a new effective adaptive non-linear filter is proposed which gives better performance in comparison with VMF, SMF, ROAMF and DBA in terms of PSNR, MSE, RMSE, SSIM and TIME 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 standard grayscale images and color images that yield recognizable and patches free restoration. The significant difference in PSNR, MSE, RMSE, 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.

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## AUTHOR PROFILE

Abdul Saleem has done B.Sc. Physics from St. John's College, Palayamkottai,M.Sc. Physics from Jamal Mohamed College (Autonomous), Tiruchirappalli, Affiliated to Bharathidasan University, MCA from Manonmaniam Sundaranar University, Tirunelveli. Currently he is working as an Assistant Professor of Computer Science, Jamal Mohamed College and the Part Time Research Scholar in the same college. His area of interest is Image Processing

Abdul Razak is working as an Associate Professor of Computer Science, Jamal Mohamed College, Tiruchirappalli. He has a teaching experience of 27 years. He has been guiding M.Phil. Scholars for past 18 years and Ph.D Scholars for past three years. His area of research interest include Network Security, Image Processing and Data Mining. He has published around 20 research articles in international journals.