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Robust Statistics Based Algorithm to Remove Salt and Pepper Noise in Images

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***Abstract*—**In this paper, a robust statistics based filter to remove salt and pepper noise in digital images is presented. The function of the algorithm is to detect the corrupted pixels first since the impulse noise only affect certain pixels in the image and the remaining pixels are uncorrupted. The corrupted pixels are replaced by an estimated value using the proposed robust statistics based filter. The proposed method perform well in removing low to medium density impulse noise with detail preservation upto a noise density of 70% compared to standard median filter, weighted median filter, recursive weighted median filter, progressive switching median filter, signal dependent rank ordered mean filter, adaptive median filter and recently proposed decision based algorithm. The visual and quantitative results show the proposed algorithm outperforms in restoring the original image with superior preservation of edges and better suppression of impulse noise

***Keywords*—**Image denoising, Nonlinear filter, Robust Statistics, and Salt and Pepper Noise.

I. Introduction

DIGITAL images are often corrupted by different types of noise, namely, additive white Gaussian noise, impulse noise and mixed (Gaussian and impulse) noise. Noises are added in the image during acquisition by camera sensors and transmission in the channel. Hence, image denoising is one of the most common and important image processing operations in image and video processing applications.

Linear filters were the primary tools for many of the signal and image processing applications, because of the availability of systematic theory for design and analysis [1]. If images are corrupted by Additive White Gaussian Noise (AWGN) linear filters show very good performance [2]. However, linear filters cannot cope with nonlinearities of the image formation model and cannot take into account the nonlinearities of human vision. Furthermore, human vision is very sensitive to high-frequency information. Image edges and image details (e.g. corners and lines) have high frequency content [3] and carry very important information for visual perception. Filters having good edge and image detail preservation properties are highly suitable for digital image filtering. Most of the digital images require low-pass filtering [4]**.** Low pass filtering tends to blur edges and destroy lines, edges, and other fine image details. These reasons have led researchers to the use of nonlinear filtering techniques for image processing applications.

An important non linear filter that will preserve the edges and remove impulse noise is standard median filter [5] [6] [7]. Median filter replaces every pixel by its median value from its neighborhood and often removes desirable details in the image. Specialized median filters such as weighted median filter [8], center weighted median filter [9] and Recursive Weighted Median Filter (RWMF) [10] were proposed to improve the performance of the median filter by giving more weight to some selected pixel in the filtering window. But they are still implemented uniformly across the image without considering whether the current pixel is noise free or not. Therefore, a noise-detection process to discriminate between uncorrupted pixels and the corrupted pixels prior to applying nonlinear filtering is highly desirable. Some of the decision based algorithms, such as Adaptive Median Filter [11], Signal Dependent Rank Ordered Mean Filter [12], Tri-State Median Filter (TSMF) [13], Progressive Switching Median filter [14], Multi-State Median Filter (MSMF) [15], Noise Adaptive Soft Switching Median Filter (NASSMF) [16], a Difference Type Noise Detector [17], Detail Preserving Filter [18], High Probability Noise Removal Filter [19] have been reported in the literature. These algorithms first detect the noisy pixels and remove it by applying either standard median filter or its variants. These filters are effective in removing low to medium density impulse noise.

Recently, a decision based algorithm (DBA) [20] has been proposed to remove high density salt and pepper noise, in which, the corrupted pixels are replaced by either the median value of the window or neighbourhood pixel, in contrast to other existing algorithms that use only median value for replacement of corrupted pixels. At higher noise densities, the median value may also be a noisy pixel, in which case, neighbourhood pixel is used for replacement from the previously processed window. The main drawback of this method is that the quality of the restored image degrades as the noise level increases above 60%. Since neighbourhood pixel value is used for replacement, when median value

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remains to be corrupted one, streaking in the image becomes persistent.

In this paper, a new robust estimation based filter is presented to remove salt and pepper noise effectively up to a noise density of 70%. It removes low to medium density impulse noise and preserves edges compare to other methods very satisfactorily.

The outline of this paper is as follows. Section II discusses the impulse noise model. Section III describes robust statistics. Section IV discusses the proposed algorithm to remove impulse noise. Section V deals results and discussions and conclusion is presented in section VI.

II. Impulse Noise Model

The Salt and Pepper (SP) noise is also called as fixed-valued impulse noise will take a gray level value either minimal (0) or maximal (255) (for 8-bit monochrome image) in the dynamic range (0-255) [12] [20] [21]. It is generated with the equal probability. In the case of salt and pepper noise, the image pixels are randomly corrupted by either 0 or 255. That is, for each image pixel at location (i,j) with intensity value $O_{i,j}$, the corresponding pixel of the noisy image will be $X_{i,j}$, in which the probability density function of $X_{i,j}$ is

$$\rho(x)=\begin{cases} p/2 & \text{for } x=0 \\ 1-p & \text{for } x=O_{i,j} \\ p/2 & \text{for } x=255 \end{cases} \quad (1)$$

where p is the noise density.

III. Robust Statistics

In statistics, classical methods depend heavily on assumptions which are often not met in practice. Robust statistics seeks to provide methods that emulate classical methods, but which are not unduly affected by outliers or other small departures from model assumptions.Robust statistics have recently emerged as a family of theories and techniques for estimating the parameters while dealing with deviations from idealized assumptions.

The noise in an image is considered as a violation of the assumption of spatial coherence of the image intensities and is treated as an outlier random variable [22]. The linear filter estimation technique is designed under the assumption of wide-sense stationary signal and noise. For most of the natural images, this condition is not satisfied. In the past, many of the noise removing filters were designed with the stationarity assumption. These filters remove noise but tend to blur edges and fine details. Recently, nonlinear estimation techniques have been gaining popularity for the problem of image denoising. Based on non-stationary assumption, a noise adaptive soft switching algorithm [13] has been proposed to remove impulse noise in images. This algorithm fails to remove impulse noise in high frequency regions such as edges in the image.

To overcome these difficulties, a nonlinear estimation technique for the problem of image denoising has been developed, based on robust statistics. A robust parameter estimation algorithm [23] has been developed for the image model that contains a mixture of Gaussian and impulsive noise. Recently, some new filters [24], [25] and [26] have been proposed for removing mixed and heavy tailed noise based on robust statistics. In [27] and [28] Black et al have used Robust estimation to deal with intensity discontinuities in natural images and apply their robust formulation to smooth the noisy image while assuming that the only outliers in the image are those due to the intensity discontinuities. Recently, a robust estimation based filter [22] has been reported in the literature to remove low to medium density Gaussian noise in natural images with detail preservation.

A. M-Estimators

The M-estimators were initially proposed by Huber (1964) [29] as a generalization of the maximum likelihood estimator. The M- estimator addresses the problem of finding best fit to the model $d=\{d_0,d_1,d_2,...,d_{S-1}\}$ to another model $e=\{e_0,e_1,e_2,...,e_{S-1}\}$ in cases where the data differs statistically from the model assumptions [1]. It finds the value that minimizes the size of the residual errors between d and e. This minimization can be written as

$$\min \sum_{s\in S} \rho((e_s-d_s),\sigma) \quad (2)$$

where σ scale parameter that controls the outlier rejection is point, and ρ is M-estimator. Reducing ρ will cause the estimator to reject more measurements as outliers.

To minimize above, it is necessary to solve the following equation

$$\sum_{s\in S} \psi((e_s-d_s),\sigma)=0 \quad (3)$$

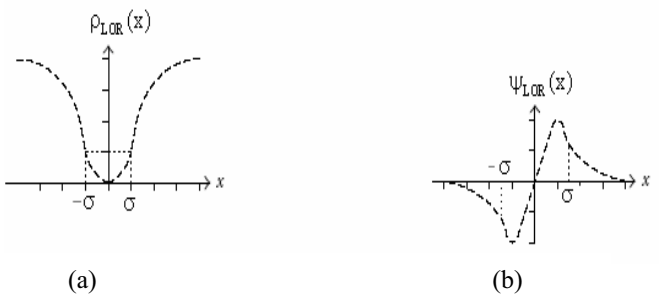
$$\text{where} \quad \psi(x,\sigma)=\frac{\partial \rho(x,\sigma)}{\partial x} \quad (4)$$

There are several types of M estimators available to solve equation (2); selection of estimator depends on measurement of robustness. Generally, robustness is measured using two parameters: influence function and breakdown point. The influence function gives the change in an estimate caused by insertion of outlying data as a function of the distance of the data from the (uncorrupted) estimate. Breakdown point is the largest percentage of outlier data points that will not cause a deviation in the solution. The least-squares approach has a breakdown value of 0%, because introducing a single outlier in the data sample will cause a deviation in the estimate from the desired solution. A robust estimator, however, may have a breakdown value of up to 50% [30].

To increase robustness, an estimator must be more forgiving about outlying measurements. In the proposed work, redescending estimators are considered for which the influence of outliers tends to zero with increasing distance [27]. Lorentzian estimator [31] [32] has an Influence function which tends to zero for increasing estimation distance and maximum breakdown value (shown in the Figure 1);

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therefore, it can be used to estimate the original image from noise corrupted image.



(a) (b)

Fig. 1 (a) Lorentzian Estimator (b) Lorentzian Influence Function

The Lorentzian estimator is defined by

$$\rho_{LOR}(x) = \log(1 + \frac{x^2}{2\sigma^2}) \quad (5)$$

and it is described by the influence function

$$\Psi_{LOR}(x) = \rho'_{LOR}(x) = \frac{2x}{2\sigma^2 + x^2} \quad (6)$$

where x is the Lorentzian estimation distance and σ is the breakdown point. Robust estimation based filter is applied to estimate image intensity values in image denoising. Image model is assumed as non stationary and, thus, the image pixels are taken from fixed windows and robust estimation algorithm is applied to each window.

IV. Proposed Algorithm

Let X denote the noise corrupted image and for each pixel X (i,j) denoted as $X_{i,j}$ a sliding or filtering window of size (2L+1) X (2L+1) centered at $X_{i,j}$ is defined as shown in figure2. The elements of this window are $S_{i,j} = \{X_{i-u, j-v}, -L \leq u,v \leq L\}$.

X(i-1,j-1)	X(i-1,j)	X(i-1,j+1)
X(i,j-1)	X(i,j)	X(i,j+1)
X(i+1,j-1)	X(i+1,j)	X(i+1,j+1)

Fig. 2 A 3 x 3 Filtering window with X(i,j) as center pixel

1. Set the minimum window size w=3;
2. Read the pixels from the sliding window and store it in S.
3. Compute minimum (S_{min}), maximum (S_{max}) and median value (S_{med}) inside the window.
4. If the center pixel in the window X(i,j) is such that Smin<X(i,j)<Smax, then it is considered as uncorrupted pixel and retained. Otherwise go to step5.
5. Select the pixels in the window such that $S_{min}<S_{ij}<S_{max}$ if number of pixels is less than 1 then increase the window size by 2 and go to step2 ,else go to step 6.
6. Difference of each pixel inside the window with the median value (S_{med}) is calculated as x and applied to robust influence function.

$$f(x)=2x/(2\sigma^2+x^2) \quad (7)$$

where σ is outlier rejection point, is given by,

$$\sigma = \frac{\tau_s}{\sqrt{2}} \quad (8)$$

where τ_s is the maximum expected outlier and is given by,

$$\tau_s = \zeta\sigma_N \quad (9)$$

where σ_N is the local estimate of the image standard deviation and ζ is a smoothening factor. Here ζ=0.3 is taken for medium smoothening.

7. Pixel is estimated using equation (10) and (11),

$$S1 = \sum_{l\in L} \frac{pixel(l) * f(x)}{x} \quad (10)$$

$$S2 = \sum_{l\in L} \frac{f(x)}{x} \quad (11)$$

where L is number of pixels in the window, Ratio of S1 and S2 gives the estimated pixel value. The structure of the proposed filter is shown in figure 3.

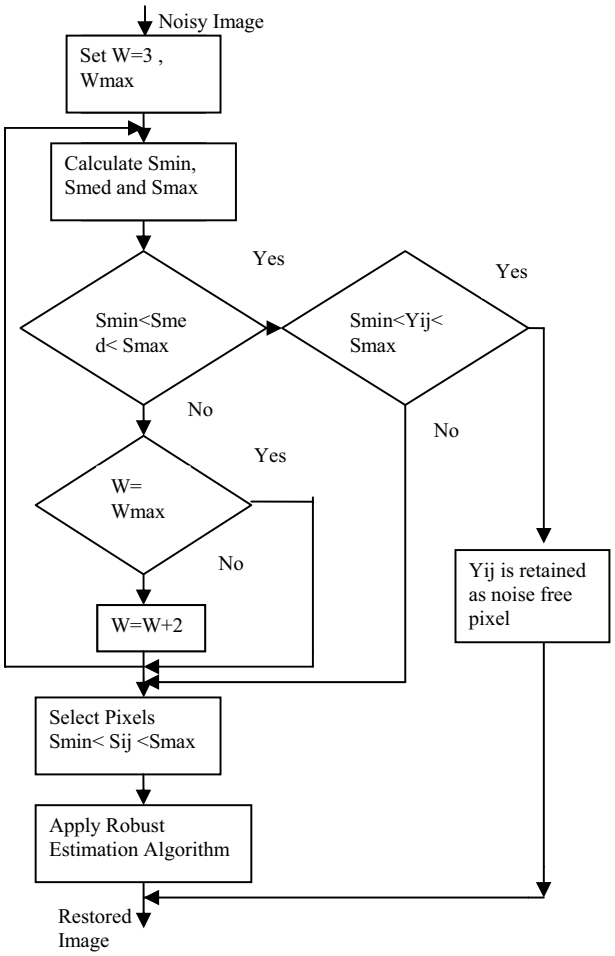


Fig. 3 Structure of the Proposed Filter

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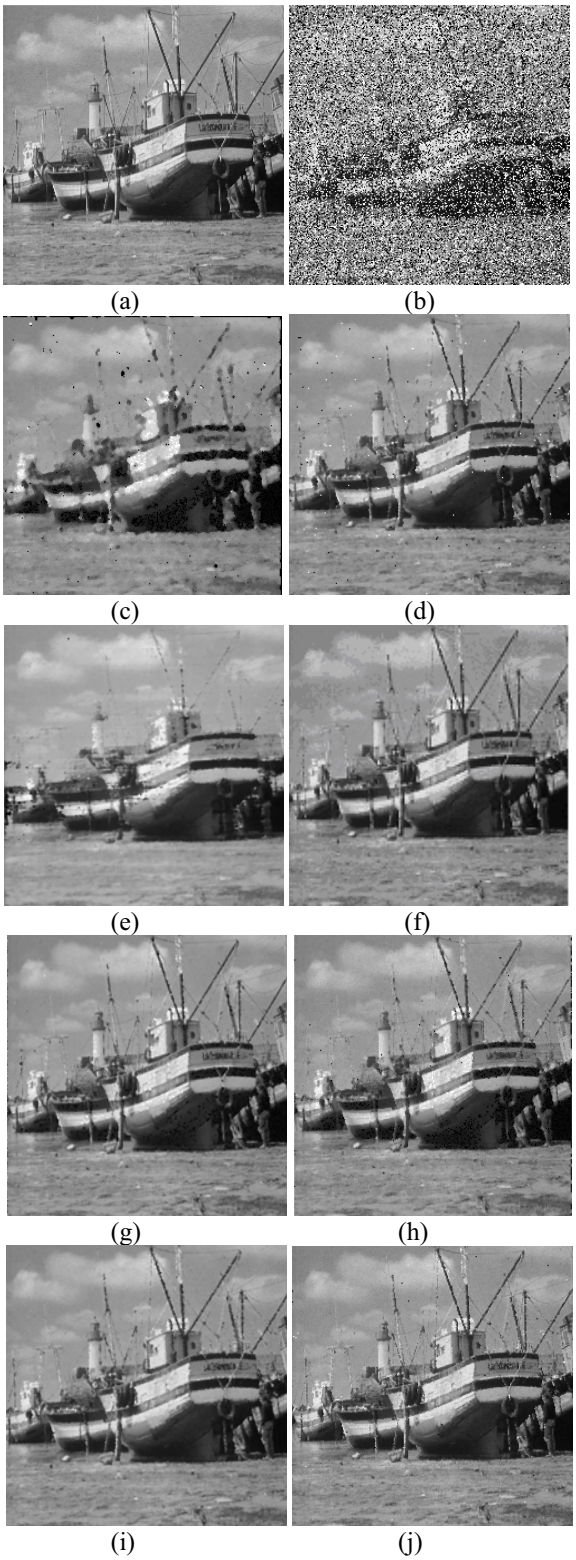


Fig. 4 (a) Original Boat image (b) Noisy image of noise density 30% (c) Standard median filter (d) Weighted median filter (e) Recursive weighted median filter (f) SD-ROM (g) Progressive switching median filter (h) Adaptive median filter (i) Decision based algorithm (j) Proposed method

V. Results and Discussions

A. Configuration

The proposed algorithm is tested using 512X512, 8-bits/pixel standard images such as Boat (Gray), Pepper (Gray), Lena (Gray) and Barbara (colour). The performance of the proposed algorithm is tested for various levels of noise corruption and compared with standard filters namely standard median filter (SMF), weighted median filter (WMF), recursive weighted median filter (RWMF), signal dependent rank ordered mean (SD-ROM) filter, progressive switching median filter (PSMF), adaptive median filter (AMF) and decision based algorithm (DPA). Each time the test image is corrupted by salt and pepper noise of different density ranging from 10 to 70 with an increment of 10 will be applied to the various filters. In addition to the visual quality, the performance of the proposed algorithm and other standard algorithms are quantitatively measured by the following parameters such as peak signal-to-noise ratio (PSNR), mean absolute error (MAE) and Mean square error (MSE).

$$PSNR=10\log_{10}\left[\frac{255^2}{\frac{1}{MN}\sum_i\sum_j (r_{ij}-x_{ij})^2}\right]$$

$$MAE=\frac{1}{MN}\sum_i\sum_j |r_{ij}-x_{ij}|$$

$$MSE=\frac{1}{MN}\sum_i\sum_j (r_{ij}-x_{ij})^2$$

where $r_{i,j}$ and $x_{i,j}$ denote the pixel values of the restored image and the original image respectively and M x N is the size of the image. All the filters are implemented in MATLAB 7.1 and filtering window used for median filter, weighted median filter, recursive weighted median filter and decision based algorithm is of size 3x3. The threshold value of the PSM and SD-ROM filters are tuned to give best performance in terms of PSNR, MAE and MSE.

B. Denoising Performance

The denoising performance of the proposed algorithm and other standard methods are tested for gray scale images and colour image. The visual quality results are presented in figure 4, 5 and 6. Figure 4(a),5(a) and 6(a) shows the original Boat, Pepper and Lena images. Figure 4(b),5(b) and 6(b) shows the noisy image of noise density 30, 50 and 70 respectively. Figure 4(c),5(c),6(c)-4(i),5(i),6(i) shows the restoration results of standard algorithms such as SMF, WMF, RWMF, SD-ROM, PSMF, AMF, and DBA. Figure 4(j), 5(j) and 6(j) shows the restoration results of the proposed filter.

The quantitative performances in terms of PSNR, MAE and MSE for all the algorithms are given in Table II to Table IV. The same are plotted in figures 7-9. For lower noise density upto 30% almost all the algorithms perform equally well in removing the salt and pepper noise completely with edge preservation as shown in the figure 3(c)-3(j). For the case of

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noise density 50%, the standard algorithms such as SMF, WMF, RWMF, SD-ROM, PSMF are fails to remove the salt and pepper noise completely. But the AMF, DBA and proposed method completely remove noise as shown in the figure 5(h),5(i) and 5(j).

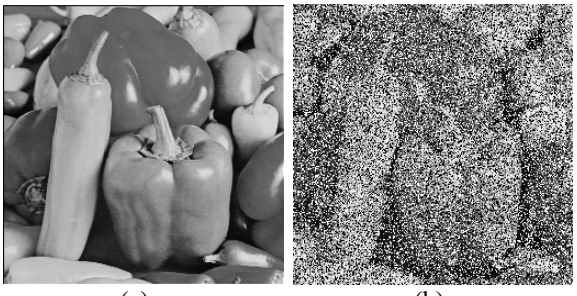
In the case of high density noise, the performance of the standard methods is very poor in terms of noise cleaning and detail preservation. For the case of 70% noise density the PSMF, AMF, and DBA perform slightly less than that of the proposed filter in terms of noise removal and edge preservation as shown in the figure 6(g)-6(j). The maximum window size of 17 x 17 is selected for AMF to give best result at high density noise level. At high density noise level the recently proposed decision based algorithm produce streaking effect at the edges as shown in figure6(i). the visual quality, PSNR, MAE and MSE results clearly show that the proposed filter outperforms than the many of the standard filters and recently proposed methods.

C. Computational time

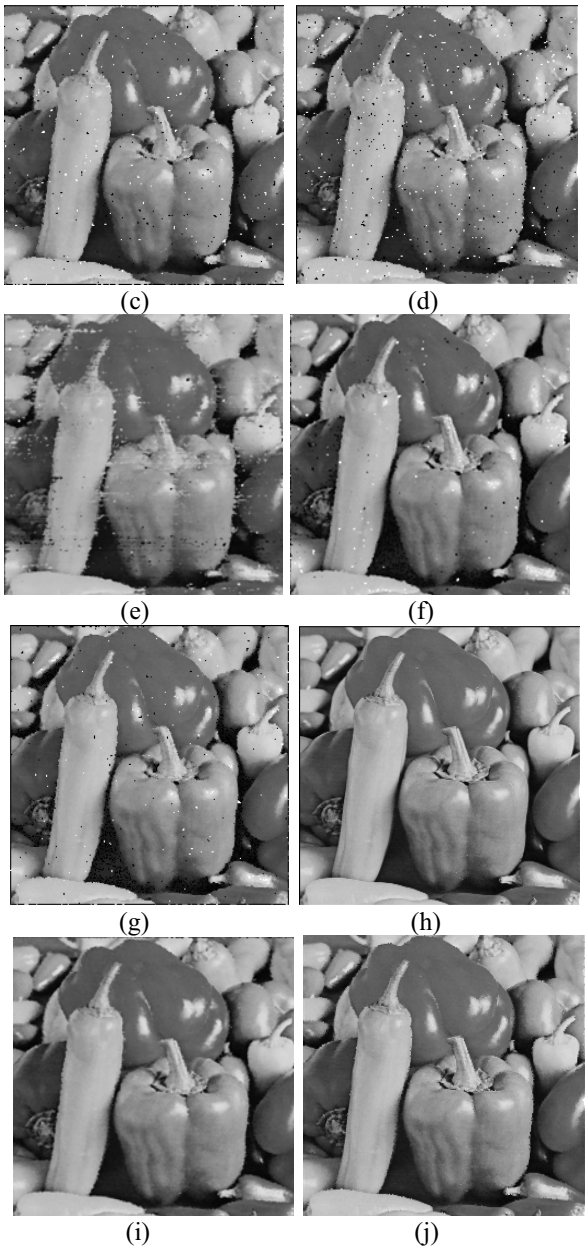
The CPU time of the proposed algorithm is compared with the standard filters is given in the Table I. For the case of comparison Lena image is corrupted with salt and pepper noise of density 70% and applied to all the filters. All the algorithms are implemented in MATLAB 7.1 on a PC equipped with INTEL 2.4 -GHz CPU and 256 MB RAM memory. The computation time of the proposed filter is slightly higher than the decision based algorithm since the proposed algorithm is uses adaptive filtering window instead of fixed filtering window as in the case of DBA.

TABLE I
COMPUTATIONAL TIME IN SECONDS FOR DENOISING 70% NOISE CORRUPTED LENA IMAGE

FILTER	TIME
Standard Median Filter (SMF)	3.13
Weighted Median Filter (WMF)	7.29
Recursive Weighted Median Filter (RWMF)	38.51
Signal Dependent Rank Ordered Mean (SD-ROM) filter	158.34
Progressive switching median filter (PSMF)	34.11
Adaptive Median Filter (AMF)	54.35
Decision Based Algorithm (DBA)	27.31
Proposed Algorithm (PA)	76.07



(a) (b)



(c) (d) (e) (f) (g) (h) (i) (j)

Fig. 5 (a) Original Pepper image (b) Noisy image of noise density 50%. Restoration results of (c) Standard median filter (d) Weighted median filter (e) Recursive weighted median filter (f) SD-ROM (g) Progressive switching median filter (h) Adaptive median filter (i) Decision based algorithm (j) Proposed method

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Fig. 6 (a) Original Lena image (b) Noisy image of noise density 70%. Restoration results of (c) Standard median filter (d) Weighted median filter (e) Recursive weighted median filter (f) SD-ROM (g) Progressive switching median filter (h) Adaptive median filter (i) Decision based algorithm (j) Proposed method

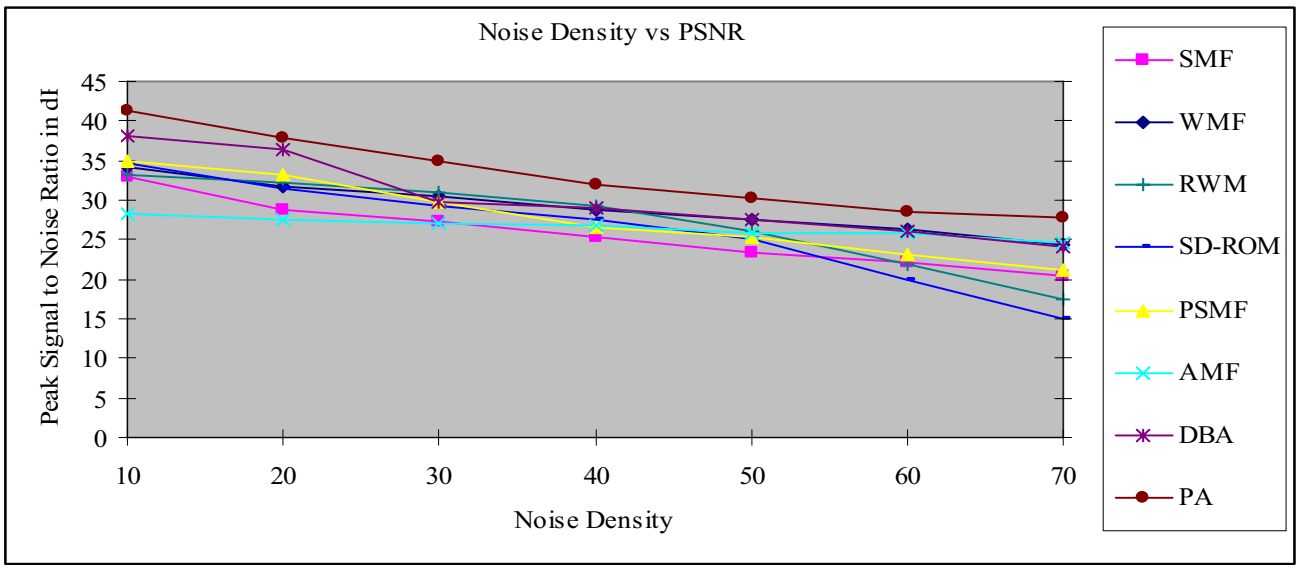


Fig.7 Comparison graph of PSNR at different noise densities for 'Lena' image

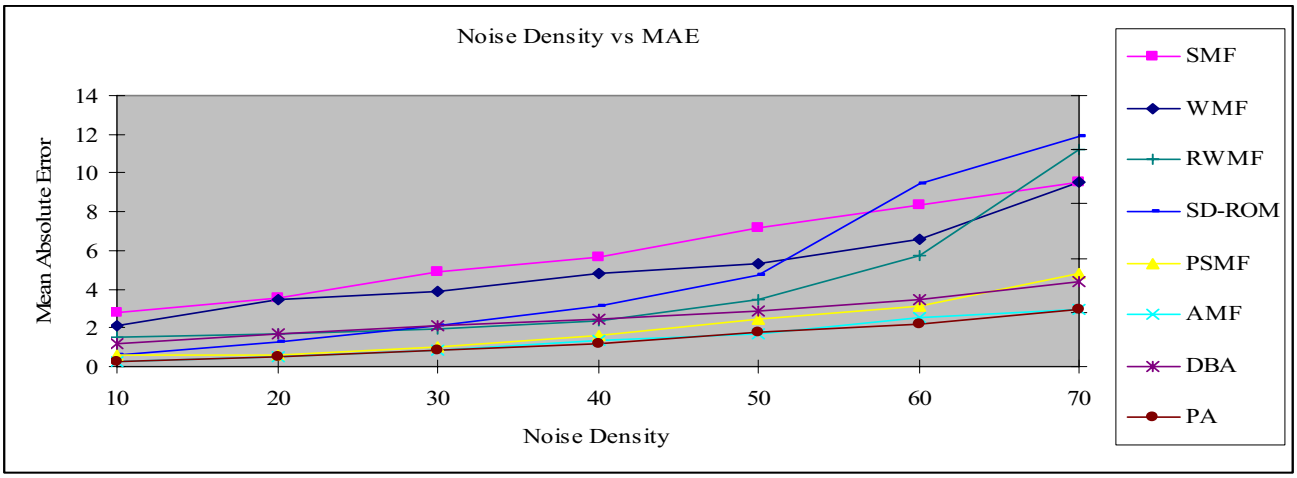


Fig. 8 Comparison graph of MAE at different noise densities for 'Lena' image

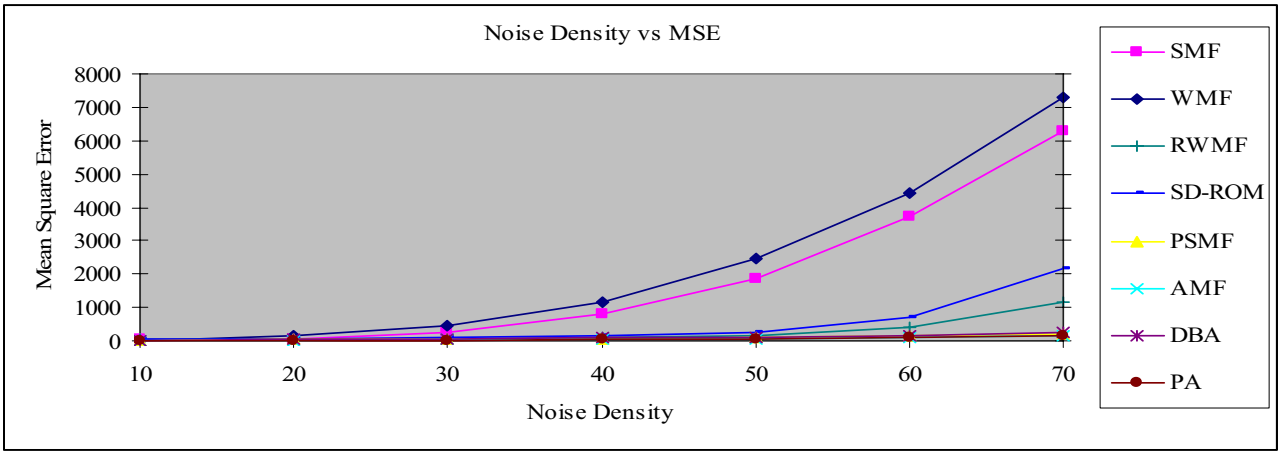


Fig. 9 Comparison graph of MSE at different noise densities for 'Lena' image

TABLE II
COMPARATIVE RESULTS OF VARIOUS FILTERS IN TERMS OF PSNR, FOR 'LENA' IMAGE

ND	SMF	WMF	RWM	SD-ROM	PSMF	AMF	DBA	PA
10	32.95	34.15	33.28	34.68	35.01	28.39	38.23	41.32
20	28.81	31.72	32.22	31.48	33.31	27.55	36.45	37.91
30	27.38	30.39	31.08	29.36	29.67	27.09	29.76	34.98
40	25.35	28.81	29.14	27.57	26.66	26.71	29.02	32.09
50	23.47	27.6	25.96	25.11	25.27	25.9	27.58	30.3
60	22.01	26.22	21.88	20.02	23.14	25.73	25.98	28.49
70	20.32	24.45	17.56	15.02	21.08	24.69	24.11	27.7

TABLE III
COMPARATIVE RESULTS OF VARIOUS FILTERS IN TERMS OF MAE FOR 'LENA' IMAGE

ND	SMF	WMF	RWMF	SD-ROM	PSMF	AMF	DBA	PA
10	2.82	2.12	1.48	0.62	0.98	0.47	2.18	0.44
20	3.55	3.49	1.68	1.28	1.09	0.95	3.05	0.93
30	4.91	3.85	1.94	2.09	1.87	1.56	3.72	1.53
40	5.67	4.79	2.4	3.12	2.84	2.38	4.4	2.18
50	7.14	5.3	3.42	4.69	4.3	3.03	5.19	3
60	8.31	6.58	5.73	9.43	5.61	4.52	6.2	3.93
70	9.51	9.51	11.23	21.89	8.53	5.24	7.78	5.21

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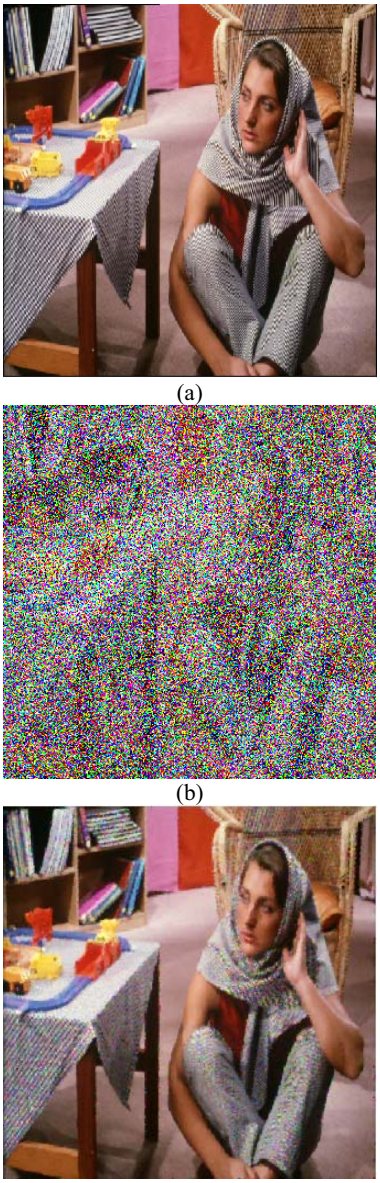
TABLE IV
COMPARATIVE RESULTS OF VARIOUS FILTERS IN TERMS OF MSE FOR 'LENA' IMAGE

ND	SMF	WMF	RWMF	SD-ROM	PSMF	AMF	DBA	PA
10	27.56	24.50	30.47	26.29	24.9	5.65	20.64	5.25
20	70.72	127.23	38.81	53.29	30.3	13.3	38.56	12.2
30	256.32	443.10	50.55	86.31	43.4	25.2	56.10	24.1
40	798.06	1135.01	79.03	133.91	70.7	51.7	81.36	40.3
50	1849.86	2455.20	164.60	235.1	94.2	61.8	113.20	60.4
60	3700.28	4447.55	421.07	715.53	133	119	163.84	88.3
70	6267.88	7305.12	1138.38	2154.5	195	175	251.85	144

D. Colour Image Denoising

The performance of the proposed filter is also tested for colour images. Generally, there are two approaches for colour image denoising, scalar median filtering approach and Vector Median (VM) filtering [10] approach. The scalar median filtering approach has been used in this paper. The RGB colour space is used in this paper to represent the colour images. In the RGB colour space, each pixel at the location (i,j) can be represented as colour vector $O_{i,j}=[O_{i,j}^{R},O_{i,j}^{G},O_{i,j}^{B}]$, where $O_{i,j}^{R}$, $O_{i,j}^{G}$, and $O_{i,j}^{B}$ are the red (R), green (G), and blue (B) components, respectively. The noisy colour images are modeled by injecting the salt and pepper noise to each of these colour components. That is, when a colour image is being corrupted by a noise density of 20 %, it means that each colour component is being corrupted by a noise density of 20%. Thus, for each pixel $O_{i,j}$, the corresponding pixel of the noisy image will be denoted as $X_{i,j}=[X_{i,j}^{R},X_{i,j}^{G},X_{i,j}^{B}]$, in which the probability density functions of each colour components is the same as the noise model described earlier.

The proposed filter is applied to the corrupted colour image, using the scalar median filtering approach. In the scalar median filtering approach, each colour component can be treated as an independent entity; that is, the same filtering scheme will be applied to R, G, and B planes independently. It considers each plane as a separate monochrome image. The filtered R, G, and B planes are to be then combined to form the recovered colour image. The performance of the proposed filter is tested for Barbara (colour) image of size 512 X 512.. Figure 10(a),10(b) and 10(c) shows the original , noisy image of noise density 70% and restored image using the proposed filter. The restored image clearly shows the proposed filter removes salt and pepper noise completely with edge and detail preservation.



(a) (b) (c)

Fig.10 (a) Original Barbara Image (b) Noisy Image of noise density70%. Restoration Result of (c) Proposed method

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VI Conclusion

A new robust statistics based filter to remove low to medium density salt and pepper noise with edge preservation in digital images is proposed in this paper. The proposed filter performs well for both gray scale and colour images. Experimental results show that the proposed method restore the original image much better than standard non linear median-based filters and some of the recently proposed algorithms. The proposed filter requires less computation time compared to other methods. The visual quality results clearly shows the proposed filter preserve fine details such as lines and corners satisfactorily. This filter can be further improved to apply for the images corrupted with high density impulse noise upto 90% and random valued impulse noise.

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References

[1] Pitas I. and Venetsanopoulos A. N., 'Nonlinear Digital Filters: Principles and Applications', Boston, MA: Kluwer Academic, 1990.
[2] Gonzalez R.C. and Woods R.E., 'Digital Image Processing', Addison-Wesley Publishing Company,2002.
[3] Bovik A.C., 'Handbook of Image and Video Processing', Academic Press, 2000.
[4] Pratt W. K., 'Digital Image Processing'. New York Wiley, 1991.
[5] Astola J and P.Kuosmanen, Fundamentals of Nonlinear Digital Filtering*, CRC Press,* 1997.
[6] Hung T.S., G.J Yang, and G.Y. Tang , 'Fast two dimensional median filtering algorithm', *IEEE Transactions on Acoustics Speech and Signal Processing* , vol. 1 pp 13-18 , 1979.
[7] Srinivasan E. and Ebenezer D., 'New Nonlinear Filtering Strategies for Eliminating Short and Long Tailed Noise in Images with Edge Preservation Properties', *International Journal of Signal Processing*, Vol.4, No.3, pp. 175- 181, 2007.
[8] Brownrigg D.R.K., 'The weighted median filter,' *Communication, ACM*, Vol. 27, No.8, pp. 807-818, 1984.
[9] Ko S.J. and Lee Y.H., 'Center weighted median filters and their applications to image enhancement,' *IEEE Trans. Circuits Systems,* Vol. 38, No. 9, pp. 984 – 993, 1991.
[10] Arce G. and Paredes J., 'Recursive Weighted Median Filters Admitting Negative Weights and Their Optimization', *IEEE Trans. on Signal Processing*, Vol. 48, No. 3, pp. 768-779, 2000.
[11] Hwang H. and Haddad R. A., 'Adaptive median filters: new and results', *IEEE Trans. on Image Processing*, Vol. 4, No.4,pp. 499-502, 1995.
[12] Abreu E., Lightstone M. and Mitra S.K., 'A New Efficient Approach for the Removal of Impulse Noise from Highly Corrupted Images', *IEEE Trans. on Image Processing,*Vol.5,No.6,pp. 1012-1025, 1996.
[13] Tao Chen, Kai-Kuang Ma and Li-Hui Chen (1999), 'Tri-State Median Filter for Image Denoising', *IEEE Trans. on Image Processing,* Vol. 8, No.8, pp.1-3, 1999.
[14] Z. Wang and D. Zhang, "Progressive switching median filter for the removal of impulse noise from highly corrupted imges", *IEEE Transactions on Circuits and Systems II*, Vol.46 pp 78-80, 1999.
[15] Tao Chen and Hong Ren Wu, 'Space Variant Median Filters for the Restoration of Impulse Noise Corrupted Images', *IEEE trans. on circuits and systems II: analog and digital signal processing*, Vol. 48, No. 8, pp.784 -789, 2001.
[16] How-Lung Eng and Kai-Kuang Ma, 'Noise Adaptive Soft-Switching Median Filter', *IEEE Trans. On Image Processing,* Vol. 10, No. 2, pp. 242 – 251, 2001.
[17] Yuan S.Q. and Tan Y.H., 'Difference-type noise detector for adaptive median filter', *Electronics letters,* Vol. 42, No.8, pp. 454 – 455, 2006.
[18] Wenbin Luo, 'An Efficient Detail-Preserving Approach for Removing Impulse Noise in Images', *IEEE signal processing letters,* Vol. 13, No.7, pp. 413 – 416, 2006.
[19] Deng Ze-Feng, Yin Zhou-Ping, and Xiong You-Lun, 'High Probability Impulse Noise-Removing Algorithm Based on Mathematical Morphology', *IEEE signal processing Letters.*, Vol. 14, No.1, pp.31-34.,2007.
[20] Srinivasan K. S. and Ebenezer D., 'A New Fast and Efficient Decision-Based Algorithm for Removal of High-Density Impulse Noises' *IEEE signal processing letters,* Vol. 14, No. 3, pp.189 -192, 2007.
[21] Raymond H. Chan, Chung-Wa Ho, and Mila Nikolova, 'Salt-and-Pepper Noise Removal by Median-Type Noise Detectors and Detail-Preserving Regularization', *IEEE Trans. on Image Processing,* Vol.14, No.10, pp.1479-1485, 2005.
[22] Rabie, "Robust Estimation Approach for Blind Denoising", *IEEE Trans. Image Processing, vol.14*, no.11, pp.1755-1765, 2005.
[23] Kashyap R. and Eom K (1988), 'Robust image modeling techniques with an image restoration application', *IEEE Trans. Acoust., Speech, Signal Processing* , Vol. 36, No. 8, pp. 1313-1325, 1988.
[24] A. Hamza and H. Krim, "Image denoising: A nonlinear robust statistical approach", *IEEE Trans. Signal Process.*, vol. 49, no. 12, pp. 3045–3054, Dec. 2001.
[25] Sardy S., Tseng P., and Brace A., 'Robust Wavelet Denoising', *IEEE Trans. Signal Processing.,* Vol. 49, No. 6, pp. 1146-1152, 2001.
[26] Ponomaryov V.I, Funes F. J. G, Pogrebnyak O.B, and De Rivera L. N., 'Denoising robust image filter with retention of small-size details in presence of complex noise mixture,' in *Proc. SPIE Conf. Visual Communications and Image Processing,* Vol. 4671 II, San Jose, CA, pp. 877-887, 2002.
[27] Black M.J. and Rangarajan A. (1994), 'The outlier process: Unifying line Processes and robust statistics', *IEEE Conf. Computer Vision and Pattern Recognition*. [Online]. Available: citeseer.nj.nec.com/ black94outlier.html
[28] Black M.J., Guillermo Sapiro, David Marimont, and David Heeger (1998), 'Robust Anisotropic Diffusion', *IEEE Trans. on Image Processing,* Vol. 7, No.3, pp. 421- 432, 1998.
[29] Huber P.S., 'Robust Statistics', John Wiley,1981.
[30] Hampel F.R., Ronchetti E.M., Rousseeuw P.J. and Stahel W.A., 'Robust Statistics: The Approach Based on Influence Functions', New York: Wiley, 1986.
[31] Black M.J., 'Robust Incremental Optical Flow', PhD thesis, Yale University, New Haven, CT, Research Report YALEU/ DCS/RR-923, 1992.
[32] Black M.J and A. Rangarajan, "On the unification of line processes, outlier rejection, and robust statistics with applications to early vision," *International Journal of Computer Vision,* Vol.19 , pp. 57–91, 1996.



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