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AN EFFECTIVE APPROACH FOR SUPPRESSING HIGH DENSITY NOISE IN IMAGE BY ROBUST ESTIMATOR

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ABSTRACT

In this paper a novel method for effectively denoising the extremely corrupted image by fixed value impulse noise using robust estimation based filter is proposed. The proposed algorithm classifies the pixels of localized window in to "corrupted" or "uncorrupted" and removes only corrupted pixels by robust estimation or by left modified neighbor. It is shown that the proposed filter effectively removes the impulse noise while preserving the good image quality. The visual and quantitative results proves that the performance of proposed filter in the preservation of edges and details is better even at noise level as high as 95%.

Index Terms: *Robust estimation, High density impulse noise, nonlinear filter.*

INTRODUCTION

Digital images could be contaminated by impulse noise during acquisition or transmission. The intensity of impulse noise has the tendency of being either relatively high or low. Thus, it could severely degrade the image quality and cause some loss of image information details. Filtering a digital image to attenuate noise while keeping the image details preserved is an essential part of image processing. Various filtering techniques have been proposed for removing impulse noise in the past and it is well-known that linear filters could produce serious image blurring. As a result, nonlinear filters have been widely exploited due to their much improved filtering performance, in terms of impulse noise attenuation and edge / details preservation. However, one of the simplest is median filter and its variants have shown superior performance to linear filter. One of the most popular and robust nonlinear filter is the *standard median* (SM) filter [1], which exploits the rank-order information of the pixel intensities within a filtering window and replaces the center pixel with the median value. However, it suffers the draw back of removing important image details. Finding a method that is efficient in both noise reduction and detail preservation is an active area of research. To trade off detail preservation against noise reduction, some solutions have been proposed in the literature. The *weighted median* (WM) filter [2], that uses weights to control the filtering behavior preserves features of given shapes and size [3]. The *center-weighted median* (CWM) filter [4,10] only weights the center pixel of the filtering window. The *tri-state median filter* [5] and the *soft switching median filter* [6] incorporate SM and CWM filter into a noise detection frame work to enhance the noise attenuation while preserving the detail. Other approaches based on the noise detection procedure include the min-max filter [7] and switching-based median filters [8, 9, 11,12]

In case of image corrupted by fixed value impulse noise, the noise pixel can take only the maximum and the minimum values in the dynamic range [9]. Early-developed switching median filters are commonly found being non-adaptive to an unknown noise. These switching median filters are prone to yielding pixel misclassification especially at higher noise density interference. To address this issue, *noise adaptive soft switching median* (NASM) filters was proposed [6]. NASM achieve a fairly robust performance in removing impulse noise, while preserving signal details across a wide range of noise densities, ranging from 10% to 50%. However, for those

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corrupted images with noise density greater than 50% the quality of the recovered image became significantly degraded [6]. In this paper, a novel robust estimation based filter is proposed to remove fixed value impulse noise effectively. The proposed filter removes low to high density fixed value impulse noise with edge and detail preservation up to noise density of more than 90%.

The outline of this paper is as follows:

Section II discusses the previous work, section III discusses the proposed algorithm to remove fixed value impulse noise. Section IV compares the result of proposed method with previous method and conclusion is presented in section V.

II. BACKGROUND

In recent times, nonlinear estimation techniques have been gaining popularity in image denoising problems. But they fail to remove noise in high frequencies regions such as edges in the image.

To over come this problem a nonlinear estimation technique has been developed based on robust statistics. The contaminating noise in an image is considered as a violation of assumption of spatial coherence of the image intensities and is treated as an outlier random variable [13,14]. When the ideal assumptions of a system are violated, problem of estimation can be solved by robust statistics technique. In [13,14] a robust estimation based filter is proposed to remove low to medium density Gaussian noise with detail preservation. In this paper robust estimation based filter is proposed to remove low to high density impulse noise by using maximum of 7 x 7 window size, which avoids the blurring effect in image.

Robustness is measured using two parameters; influence curves and breakdown point. The influence curves tell us how an infinitesimal proportion of contamination affects the estimate in large samples. The breakdown point is the largest possible fraction of observations for which there is a bound on the change of the estimate when that fraction of the sample is changed without restrictions.

If an estimator is more forgiving about outlying measurements, then robustness increases. In this paper, the re-descending estimators are considered for which the influence of outliers tends to zero with increasing distance [8]. A Lorentzian estimator has an influence function which tends to zero for increasing estimation distance and maximum breakdown value; therefore it can be used to estimate the original image pixel from noise corrupted image pixel.

The Lorentzian estimators and its influence functions are given by equation (1) and (2).

$$\rho(x) = \log\left(1 + \frac{x^2}{2\sigma^2}\right) \tag{1}$$

$$\psi_{lorentz}(x) = \frac{2x}{\left(2\sigma^2 + x^2\right)} \tag{2}$$

This estimator is applied to estimate image intensity values in image denoising. Image model is assumed to be non stationary, thus the image pixels are taken from fixed window and this estimation algorithm is applied to each window, of maximum size of 7 x 7. If the window size is more than this, then the noise pixel is replaced by left processed neighbor.

III PROPOSED ALGORITHM

The proposed approach processes the corrupted image after detecting the impulse noise. The detection of noisy and noise-free pixels is decided by checking whether the value of a current pixel lies between the maximum, minimum and median value in the selected window. If the median pixel and the current pixel lie inside the dynamic range [0, 255], then it is considered as noise free pixel, and it is left unchanged. Other wise it is considered as noisy pixel and is replaced by Lorentzian estimator's value of window, if the window size is up to 7 x 7. If size is more than 7 x 7, the pixel is replaced by its processed left neighborhood pixel value.

Let 'B' denotes the corrupted image. For each pixel B(x y), a 2-D sliding window Sxy of size 3 x 3 is selected such that the current pixel B(x y) lies at the center of the sliding window. Let Pmin, Pmed and Pmax are the minimum, median and maximum gray levels in the selected window.

The proposed algorithm is as follows.

STEP 1— Initialize WS = 3 (WS = window size)

STEP 2— Compute Pmin, Pmed and Pmax in Sxy

STEP 3— If Pmin< Pmed < Pmax, then go to step 6.

Other wise increase the window size, as WS=WS+2, until the maximum window size is reached. Here the maximum size is 7 × 7.

STEP 4 --- If WS $\leq$ WS (7 x 7), go to step 2, else replace the center pixel by left neighborhood pixel value.

STEP 5 --- If Pmin< B(x y) < Pmax, then B(x y) is not a noise pixel, else select pixel in the window such that Pmin< S(x y) < Pmax and go to step 6.

STEP --- 6 The value of 'x_l' is calculated for a selected window, which represent the difference of each pixel inside the window with respect to median value. Then the influence function $\psi(x_l)$ is calculated by equation

$$\psi(x_l) = \frac{2x_l}{\left(2\sigma^2 + x_l^2\right)} \tag{3}$$

where 'ó' is outlier rejection point, given by,

$$\sigma = \frac{\tau_s}{\sqrt{2}} \tag{4}$$

where 'τ_s' is maximum expected outlier, which is calculated as,

$$\tau_s = \zeta\sigma_N \tag{5}$$

Where 'σ_N' is the local estimation of the image standard deviation, where 'æ' is a smoothening factor and is chosen as 0.3 for low to medium smoothing.

STEP 7 --- Pixel is estimated by using equation (6) and (7),

$$S_1 = \sum_{l\in L}(Pixel(l))\frac{\psi(x_l)}{x_l} \tag{6}$$

$$S_2 = \sum_{l\in L}\frac{\psi(x_l)}{x_l} \tag{7}$$

where L is the total number of pixel in the selected window, then, the ratio of S_1 and S_2 gives the estimated pixel value.

IV RESULTS

The proposed filter is tested using Lena image of 512 × 512 8 bits pixel. This is corrupted by impulse noise at various noise densities and performance is measured using the parameters like Peak-Signal-to-Noise Ratio (PSNR), Mean Absolute Error (MAE), Mean Square Error (MSE), and Universal Quality Index (UQI). They are defined by the following formula,

$$\text{PSNR} = 10\log_{10}\left(\frac{255^2}{\text{MSE}}\right) \tag{8}$$

where MSE is mean-square error given by

$$MSE = \sum_{x=1}^{M}\sum_{y=1}^{N}\left(f(x,y) - \hat{f}(x,y)\right)^2 \tag{9}$$

$$MAE = \sum_{x=1}^{M}\sum_{y=1}^{N}\left|f(x,y) - \hat{f}(x,y)\right| \tag{10}$$

$$UQI = \frac{4\sigma_{f\hat{f}}\bar{f}\bar{\hat{f}}}{(\sigma_f^2 + \sigma_{\hat{f}}^2)[(\bar{f})^2 + (\bar{\hat{f}})^2]} \tag{11}$$

Where

$$\bar{f} = \frac{1}{MN}\sum_{x}^{M}\sum_{y}^{N} f(x,y),$$

$$\bar{\hat{f}} = \frac{1}{MN}\sum_{x}^{M}\sum_{y}^{N}\hat{f}(x,y)$$

$$\sigma_f^2 = \frac{1}{MN-1}\sum_{x}^{M}\sum_{y}^{N}(f(x,y) - \bar{f})^2,$$

$$\sigma_{\hat{f}}^2 = \frac{1}{MN-1}\sum_{x}^{M}\sum_{y}^{N}(\hat{f}(x,y) - \bar{\hat{f}})^2,$$

$$\sigma_{f\hat{f}} = \frac{1}{MN-1}\sum_{x}^{M}\sum_{y}^{N}(f(x,y) - \bar{f})(\hat{f}(x,y) - \bar{\hat{f}}),$$

where MN is total number of pixels and f and $\hat{f}$ are original and filtered image respectively.

In order to check the visual quality, Lena image is corrupted by 70% impulse noise density and applied to various filters and the result is as shown in figure 1. The visual quality clearly shows that the proposed method's performance is best when compared to other filters.

Table I, II, and III shows the comparison of PSNR, MSE and UQI for Lena image corrupted by different noise densities applied to different filters. Figure 3, 4,and5 respectively shows graphical comparison of the PSNR, MSE and UQI parameter.

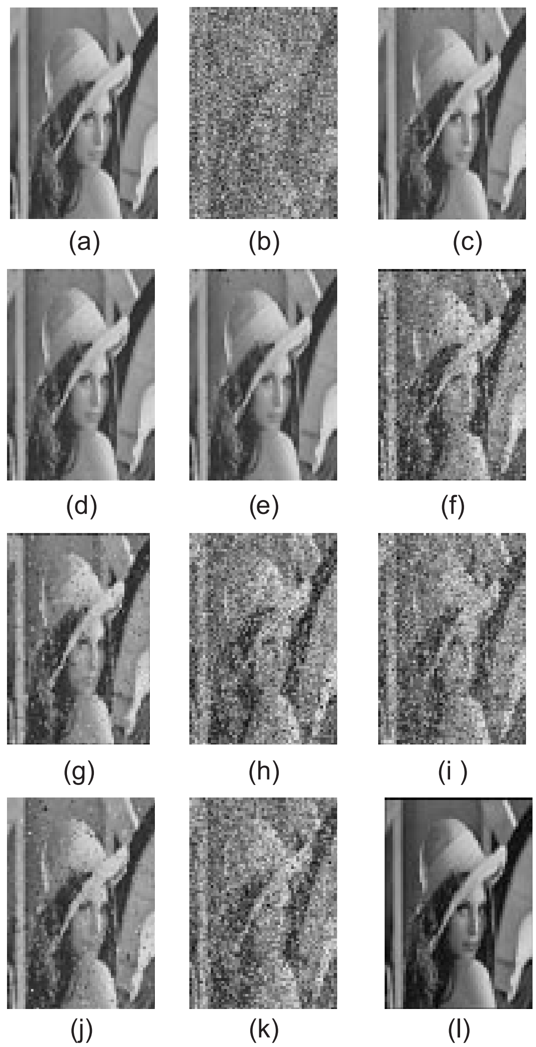


Figure 1 : (a) Original (b) Noisy Image (noise density 70%). (c)AMF(Adaptive Median Filter)3×3 (d) AMF (5×5) (e) AMF (7×7) (f) SMF(Switching Median Filter) (g) MF(Median Filter)(7×7) (h) PSMF (i) CWMF (j) ATMF(Alpha –Trim Median Filter) (k) Rank Ord.MF (l) PA (Proposed Algorithm)

From visual quality, comparison tables and graphs, the proposed filter produce better result compared to other existing methods

Table I : Comparison table of PSNR of different filter methods for Lena Image

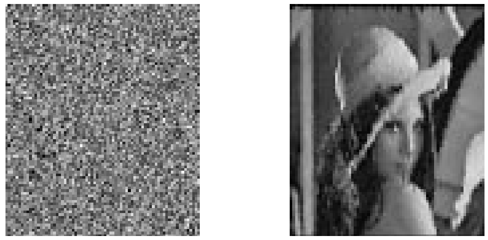
Noise Density (%)	MF (3x3)	MF (5x5)	MF (7x7)	ATMF	CWMF	Rank - Ord MF	PSMF	AM	SMF	PA
10	31.44	34.15	29.40	23.59	34.48	24.15	38.46	38.73	38.40	41.63
20	30.57	27.72	28.98	23.50	29.83	17.85	34.51	36.53	35.47	38.42
30	29.26	21.59	28.31	23.38	24.08	14.09	30.09	34.28	32.76	35.90
40	26.30	17.43	27.61	23.24	19.16	11.39	25.88	32.47	29.31	33.55
50	21.56	14.32	26.12	22.89	15.42	9.64	21.19	30.71	23.84	31.41
60	16.80	11.65	21.90	22.02	12.43	8.28	12.46	28.97	18.09	29.38
70	12.70	9.52	16.45	18.14	10.08	7.38	10.01	26.99	13.77	27.31
80	9.72	7.90	11.78	13.18	8.20	6.68	8.23	22.88	10.22	25.39
90	7.33	6.57	8.12	8.62	6.70	6.10	6.72	14.59	7.51	22.85

Table II : Comparison table of MSE of different filters for Lena Image

Noise Density (%)	MF (3x3)	MF (5x5)	MF (7x7)	ATMF	CWMF	Rank - Ord MF	PSMF	AM	SMF	PA
10	3.84×10^{-4}	7.16×10^{-4}	0.0011	0.0044	3.55×10^{-4}	0.0038	1.42×10^{-4}	1.33×10^{-4}	1.44×10^{-4}	6.87×10^{-5}
20	0.00017	8.75×10^{-4}	0.0013	0.0045	0.0010	0.0164	3.53×10^{-4}	2.22×10^{-4}	2.83×10^{-4}	1.43×10^{-4}
30	0.0069	0.0012	0.0015	0.0046	0.0039	0.0390	9.78×10^{-4}	3.72×10^{-4}	5.29×10^{-4}	2.56×10^{-4}
40	0.0180	0.0023	0.0017	0.0047	0.0123	0.0725	0.0026	5.65×10^{-4}	0.0012	4.41×10^{-4}
50	0.0370	0.0070	0.0024	0.0051	0.0287	0.1085	0.0076	8.48×10^{-4}	0.0041	7.22×10^{-4}
60	0.0683	0.0209	0.0064	0.0063	0.0571	0.1483	0.0567	0.0011	0.0155	0.0010
70	0.1114	0.0531	0.0226	0.0153	0.0981	0.1828	0.0996	0.0018	0.0420	0.0015
80	0.1618	0.1066	0.0663	0.048	0.1511	0.2156	0.1502	0.0028	0.09848	0.0019
90	0.2202	0.18848	0.1540	0.1371	0.2134	0.2452	0.2125	0.0043	0.1771	0.0040

Table III : Comparison table of UQI of different filters for Lena. image

Noise Density (%)	MF (3x3)	MF (5x5)	MF (7x7)	ATMF	CWMF	Rank-Ord MF	PSMF	AM	SMF	PA
10	0.9945	0.9897	0.9834	0.9461	0.9949	0.9528	0.9982	0.9983	0.9982	0.9992
20	0.9762	0.9874	0.9817	0.9450	0.9852	0.8178	0.9956	0.9972	0.9964	0.9984
30	0.9071	0.9830	0.9790	0.9435	0.9461	0.6435	0.9878	0.9953	0.9933	0.9971
40	0.7828	0.9668	0.9750	0.9416	0.8456	0.4662	0.9696	0.9923	0.9853	0.9950
50	0.6209	0.9053	0.9650	0.9368	0.6835	0.3360	0.9142	0.9893	0.9495	0.9919
60	0.4348	0.7502	0.9104	0.9234	0.4941	0.2196	0.5511	0.9841	0.8275	0.9871
70	0.2735	0.5082	0.7302	0.8252	0.3164	0.1369	0.3718	0.9749	0.6195	0.9794
80	0.1567	0.2853	0.4354	0.5767	0.1762	0.0698	0.2362	0.9367	0.3695	0.9683
90	0.0664	0.1157	0.1652	0.2346	0.0778	0.0263	0.1206	0.6599	0.1636	0.9437



(a) (b)

Figure 2 : (a) Lena Image corrupted by 98% Noise density (b) Filtered image by Proposed Method

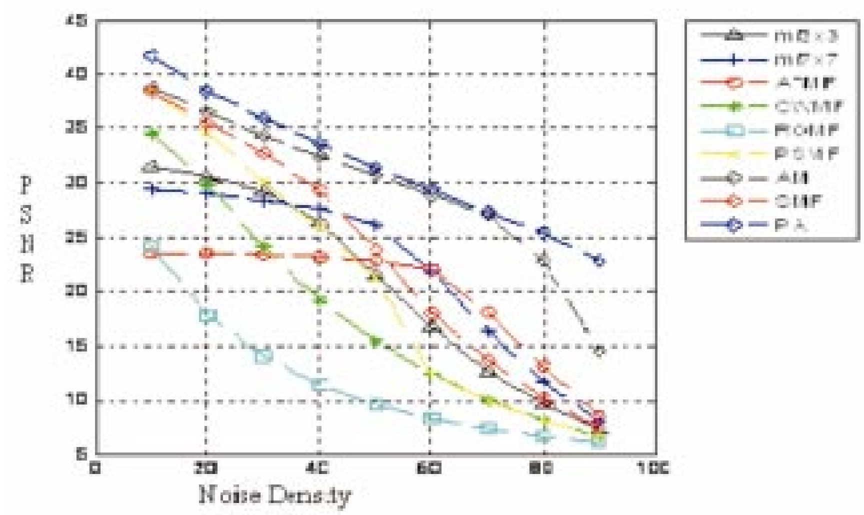


Figure 3 : PSNR plot

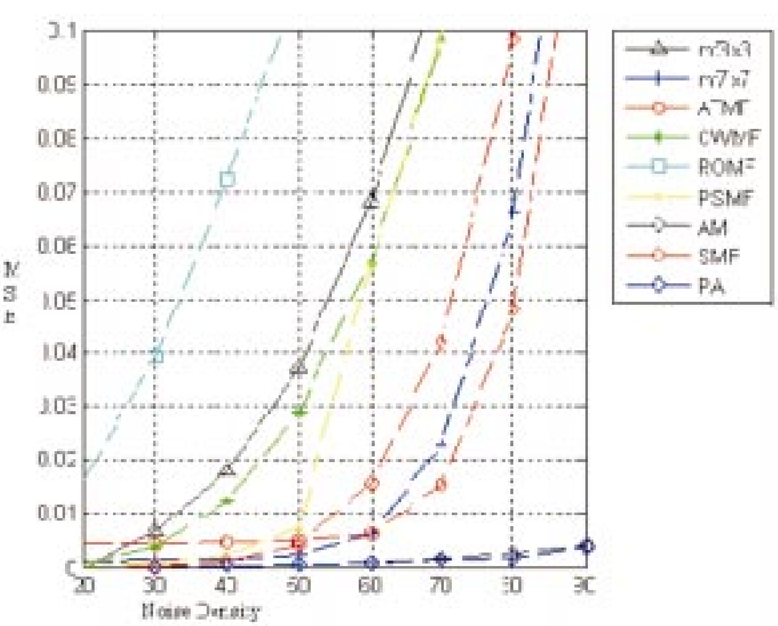


Figure 4 : MSE plot

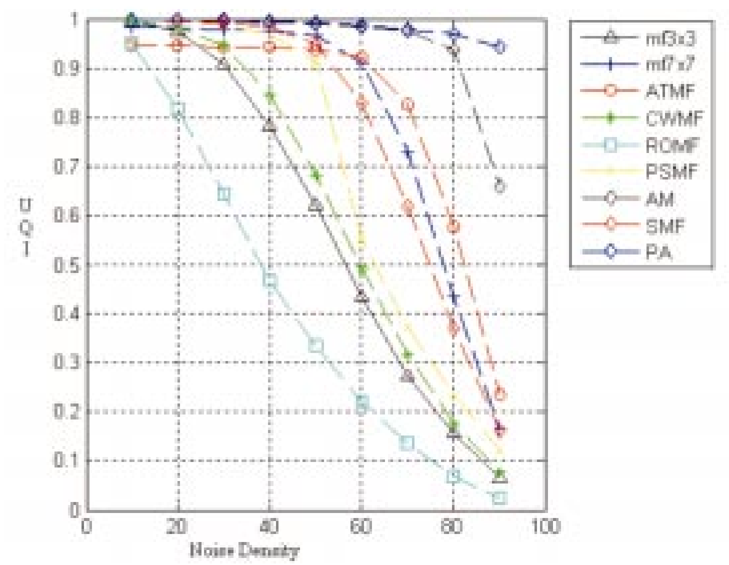


Figure 4 : UQI plot

Figure 2 shows that the proposed algorithm removes very high density impulse noise using robust estimation. An extensive experimental result shows that the proposed algorithm performs much better than the standard nonlinear median based filters. It also works even for low and medium density noise also and preserves all fine details of image.

V CONCLUSION

The proposed algorithm(PA) addresses two problems: blurring of images for large window sizes and poor noise removal for smaller window size, which are encountered in other methods. In contrast to other methods, the proposed method uses the window size 7 x 7, which reduces the blurring effect compared to the methods that use larger window size for filtering. The performance of noise removal is also better than smaller window filters. The selected window size ensures the higher correlation between pixels; this provides more edge details, leading to better edge preservation. The corrupted pixels up to 7 x 7 window sizes are replaced by robust estimator and above this window size corrupted pixels are replaced by neighboring pixel that leads to better result than other existing methods. The proposed filter also shows effective filtering performance across wide range of noise density varying from 10% to 90%.

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