An Efficient Adaptive ROAD And Robust Estimation Based De-noising Technique

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Abstract

In this paper, an algorithm for de-noising fixed value impulse noise is presented. The ROAD(Rank Ordered Absolute Difference) value computed using fixed window size 3X3 detects impulse pixel. The corrupted pixels are identified and replaced by the estimated value by Lorentzian estimator. The window size for estimation is adaptive and expands up to 7 X 7 in case of high noise densities. The noise free pixels remain unchanged. .The performance of the algorithm is evaluated using PSNR and MSE. The results prove that the method works well for high density impulse noise , preserves edges and other fine details in the image.

Key words : Noise detection, Adaptive filter, Robust estimator.

I. Introduction

Removing impulse noise is an active research area as this pre- processing step has a direct impact in the precision of all Image Processing tasks. Impulse noise is characterized by noisy spikes giving salt and pepper appearances in images are caused due to faulty memory locations, bit errors in transmission, timing errors in digitization etc.

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De-noising impulse noise has been studied over decades and many filters have been proposed. In earlier days, linear filters [9] were proposed which worked well for additive Gaussian noise but failed for impulse noise. This led the researchers to focus on non-linear filtering techniques. A class of widely used nonlinear digital filters is median filter. Median filters are known for their capability to remove impulse noise as well as preserving the edges. The main drawback of a standard median filter (SMF) is that it is effective only for low noise densities. At high noise densities, SMFs often exhibit blurring for large window sizes and insufficient noise suppression for small window sizes .

Specialized median filters such as, center weighted median filter [8]and Recursive Weighted Median Filter (RWMF) [2] 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 similar to median filters. Impulse noise introduces high frequency components in images. Human vision is very sensitive to high frequency components. Also image features such as edges and corners corresponds to high frequency values. De-noising filters should yield sufficient noise reduction without

losing the high-frequency content of image edges. To overcome this problem a test for noise detection is added to the de-nosing process. And so, the noisy pixel is replaced leaving the remainder unchanged. The resultant was Adaptive Median Filter [7], Signal Dependent Rank Ordered Mean Filter [1], Tri-State Median Filter (TSMF)

[11], Progressive Switching Median filter [14], Multi-State Median Filter (MSMF) [12], Noise Adaptive Soft Switching Median Filter (NASSMF) [5], a Difference Type Noise Detector [16], Detail Preserving Filter [15] and High Probability Noise Removal Filter. These techniques 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 and failed for high density impulse noise.

In this paper an efficient algorithm based on robust estimation is presented to remove salt and pepper noise effectively upto a noise density of 60%. The proposed algorithm uses simple fixed length window of size 3 x 3 for noise detection based on Rank

Ordered Absolute difference (ROAD) value, which clearly isolates the noisy pixel from an edge pixel. The Robust estimation holds well in retaining the local features and edges in the image and to deal with intensity discontinuities. An adaptive window is used for noise estimation and the window size is extended only in case of the absence of noise free pixels for estimation in the current window.

II. Impulse Noise Model

In grayscale images, the intensity is stored as an 8-bit integer giving 256 possible different shades of gray from black to white, which can be represented as a [0,255] integer interval.

If O(i, j) denotes the pixel value of a 2D image O at position (iI, j) and η(i, j) denote the impulse value at position (i, j) then the occurrence of impulse noise, for grayscale images can be modeled using (1) as

$$A(i,j) = \begin{cases} O(I,j) \text{ with probability } 1\text{-}pr \\ \eta\,(I,j) \text{ with probability } pr \end{cases} \qquad (1)$$

Where pr is the probability that a pixel is corrupted, and A is the corrupted image. In the case of fixed value impulse noise (salt and pepper noise), for pr there are only two, which are the maximum and the minimum pixel value in the range [0,255]

III. Rank Ordered Absolute Difference Statistic(ROAD)

The ROAD statistic [10] is a measure of how close a pixel value is to its n most similar neighbors. This technique is based on the fact that,

1) Unwanted impulses will vary greatly in intensity from most or all of their neighboring pixels.
2) Pixels composing the actual image should have at least half of their neighboring pixels of similar intensity. This is true even pixels on an edge where there is a sharp transition between the colors.

A. *Definition*

Let x=(x1,x2) be the location of the pixel under consideration and let P(N) be a set of points in a (2N+1)x(2N+1) neighborhood centered around x for some positive integer N given by

$$P(N)=\{x_{i,j},\ -N\le i,\ j\le N\} \qquad (2)$$

In this discussion we consider N=1.

Let P^0_x represents the set of points in a 3 x 3 neighborhood of x.For each yε P^0_x let $d_{x,y}$ denote the absolute difference between the pixels x and y given by,

$$d_{x,y}=|u_x-u_y| \qquad (3)$$

$d_{x,y}$ values are sorted in increasing order to define $ROAD_m(x)$ given by

$$ROAD_m(x)=\sum_{i=m1}^{m2} r_i(x) \qquad (4)$$

The value of m1 and m2 depend on the statistic of the noise free neighborhood pixels.

IV Robust Statistics

The field of robust statistics is concerned with estimation problems in which the data contains outliers. Robust estimation algorithms can be classified into three large types of estimators: M-estimator, L-estimator, and R-estimator. An M-estimator is a maximum likelihood-type estimator, and it is obtained by solving a minimization problem..

The M-estimators were initially proposed by Huber (1964)[6] 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 . It finds the value that minimizes the size of the residual errors between d and e.This minimization can be written as using the equation.

$$\min \sum_{s\in S} \rho((e_s - d_s),\sigma) \qquad (5)$$

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. S is the set of all chosen values. d_s is the input model and e_s is the best fit model.To minimize above, it is necessary to solve the equation (6) & (7)

$$\sum \Psi((e_s\text{-}d_s),\sigma) = 0 \qquad (6)$$

Where the influence function given by the equation (7),

$$\Psi(x,\sigma) = \frac{\partial \rho(x,\sigma)}{\partial x} \qquad (7)$$

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.

To increase robustness, re-descending estimators are considered for which the influence of outliers tends to zero with increasing distance [4]. Lorentzian estimator [3][4] an Influence function which tends to zero for increasing estimation distance and maximum breakdown value.

The Lorentzian estimator $\rho_{LOR(x)}$ is defined by the equation (8)

$$\rho_{LOR}(x) = \log(1+\frac{x^2}{2\sigma^2}) \qquad (8)$$

and it is described by the influence function $\psi_{LOR(x)}$ given by the equation (9)

$$\psi_{LOR}(x) = \rho'_{LOR}(x) - \frac{2x}{2\sigma^2 + x^2} \qquad (9)$$

Where x is the Lorentzian estimation distance and σ is the breakdown point.

V. Proposed Algorithm

This method uses $ROAD_m$ value for noise detection and Robust Estimation using Lorentzian estimator for noise estimation.

The technique has two phases,

(A) Impulse noise detection phase and

(B) Estimation phase.

(A) *Impulse noise detection phase*

Impulse Noise detection phase has the following steps,

1.The 3 x 3 neighborhood for each pixel is extracted.

2. The absolute differences of the centre and neighborhoods are sorted in ascending order.

3. Select the requisite values computed in the previous step to find the $ROAD_m$ value. $ROAD_m$ is based on the correlation of the pixel with its noise neighbors.

Let AD(i) be the absolute difference matrix and n the count of pixels with value p such that 0<p<255. The following test conditions are used to find the $ROAD_m$ value.

if $\sum_{i=1}^{9} AD(i) = 0$ and $n \geq 8$

$ROAD_m=0$

else if n=1

$ROAD_m = AD(8)$

else if n=2

$$ROAD_m = \sum_{i=6}^{8} AD(i)$$

else

$$ROAD_m = \sum_{i=2}^{5} AD(i)$$

4.The $ROAD_m$ value is compared with the experimentally computed threshold value for impulse detection. The threshold value used in this here is 25.

if $1 \leq ROADm \leq 25$

centre_pixel= 'noise free'

else

central_pixel= 'impulse'

The Estimation phase is executed to replace the impulse pixel with an estimated one.

(B) *Estimation phase*

Lorentzian estimator is used for estimation. The estimation phase has the following steps[13],

1.Find the no of noise free neighborhood pixels. If there is no noise free pixels extend the window size by 2 until the window size is 7X7 and select noise free pixels in the extended window.

2. Find x , the difference of each selected pixel with the median value and compute the function f(x) given in the equation (10)

$$f(x)=2x/(2\sigma +x) \quad (10)$$

Where σ is outlier rejection point, is given by the equation (11),

$$\sigma = \frac{\tau_s}{\sqrt{2}} \quad (11)$$

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

$$\tau_s = \zeta \sigma_N \quad (12)$$

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.

3.Pixel is estimated using the equations (13) and (14)

$$S_1 = \sum_{l \in L} \frac{pixel(l) * f(x)}{x} \quad (13)$$

$$S_2 = \sum_{l \in L} \frac{f(x)}{x} \quad (14)$$

Where L is number of selected pixels in the window.

6. Ratio of S_1 and S_2 gives the estimated pixel value which replaces the impulse pixel.

VI. Performance Evalution

The performance of the proposed method is evaluated using two parameters., Mean Square Error (MSE) value and Peak Signal to Noise Ratio(PSNR).

A. *Mean Square Error*

Mean Square Error Value (MSE) is a risk function, corresponding to the expected value of the squared error loss or quadratic loss. MSE measures the average of the square of the error. The error is the amount by which the estimator differs from the quantity to be estimated. In this case The MSE is the cumulative squared error between the de-noised image and the original image. Mean Square Error (MSE) is computed using the equation (15).

$$MSE = \frac{1}{MN}\sum_{y=1}^{M}\sum_{x=1}^{N}[I(x,y) - I^{'}(x,y)]^2 \qquad (15)$$

Where I(x,y) is the original image, I'(x,y) is the reconstructed image and M,N are the dimensions of the images. A lower value for MSE means lesser error

B. *Peak Signal to Noise Ratio*

The PSNR block computes the peak signal-to-noise ratio, in decibels, between two images. This ratio is often used as a quality measurement between the original and estimated image. The higher the PSNR, the better the quality of the estimated, or reconstructed image. PSNR in decibels (dB) is computed by using the equation (16)

$$PSNR = 10\log 10\left(\frac{255^2}{MSE}\right) \qquad (16)$$

Where MSE is given by equation (15)

The performance of this technique is evaluated on different noise densities and the results are presented in tables and graph This method is implemented using Matlab 7.5 and executed in the core2 duo processor 2.40GHz, 0.98 GB RAM

The quantitative results are shown in Table I for three standard images boat.jpg,lena.jpg and pepper.jpg. The quantitative results in Table I are presented graphically in Fig. 1& 2. Table I and Fig .1,2 shows that with increase in noise density the MSE values increases and PSNR value decreases. But from the consistent results on different images it is proved that the method holds well for different images it is proved that the method holds well for different images with different characteristics.

Table II gives the comparison results of the proposed method (PA) with SMF(Standard Median Filter),WMF(Weighted Median Filter) and DBA(Decision Based Algorithm) using the PSNR values and Fig.3-5 shows that for all images, the Proposed Algorithm(PA) performs well than the existing methods. Even at high noise densities the decrease in PSNR values is less when compared with the existing methods. Table III and Fig 6-8 shows that for boat.jpg and pepper.jpg,the method performs well than these existing methods and even at high noise densities the increase in MSE values is less when compard with the existing methods.

The visusl results in Fig. 9 show that the method is good in retaining edges, avoids blurring and removing noise. So it is proved that the PA is good in preserving image details, high PSNR ,low MSE values and performs effectively when compard with the given existing methods.

TABLE I

Performance of the algorithm with three different gray scale images(512 X512)

Noise	MSE values			PSNR values(db)		
	boat.jpg	Lena.jpg	pepper.jpg	boat.jpg	Lena.jpg	pepper.jpg
0%	13.71	5.24	2.40	36.75	40.93	44.32
10%	15.72	7.32	3.64	36.16	39.48	42.51
20%	18.24	10.29	5.46	35.51	38.00	40.76
30%	21.52	13.99	7.80	34.80	36.67	39.20
40%	24.84	18.54	11.43	34.17	35.44	37.55
50%	30.17	25.79	17.31	33.33	34.01	35.75
60%	36.82	35.33	23.68	32.46	32.64	34.38
70%	44.19	46.10	39.25	31.67	31.49	32.19
80%	52.24	70.72	63.14	30.95	29.63	30.13

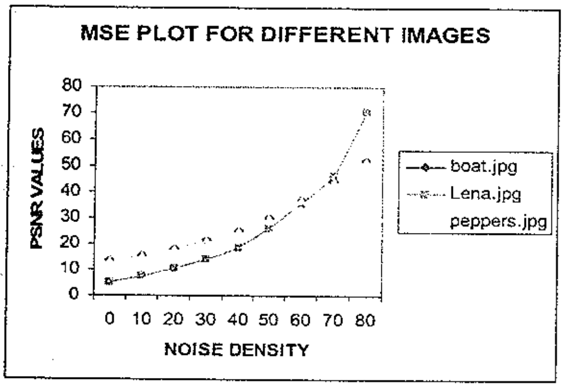

Figure 1 : MSE plot for different images

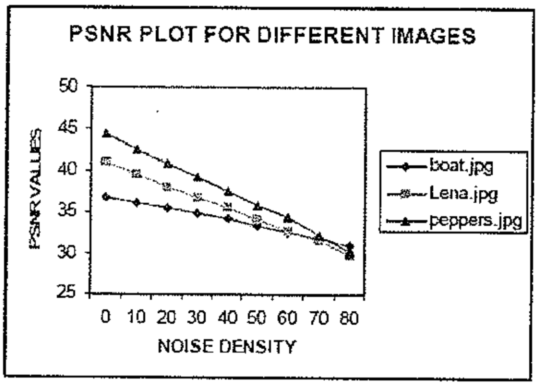

Figure 2 : PSNR plot for different images

Table II

Comparison with different Existing Methods for images(1-boat.jpg,2- Lena.jpg,3-pepper.jpg) using PSNR values

ND	SMF			WMF			DBA			PA		
	1	2	3	1	2	3	1	2	3	1	2	3
10%	27.40	27.70	28.77	30.79	34.15	31.65	32.69	38.23	34.31	36.16	39.48	42.51
20%	26.34	26.60	27.18	29.41	31.72	29.97	30.93	36.45	32.19	35.51	38.00	40.76
30%	25.75	25.86	25.86	28.64	30.39	29.20	30.10	29.76	31.03	34.80	36.67	39.20
40%	25.26	25.35	25.35	28.26	28.81	28.83	29.48	29.02	30.20	34.17	35.44	37.55
50%	25.24	24.99	24.99	27.99	27.60	28.56	29.03	27.58	29.53	33.33	34.01	35.75
60%	24.90	24.74	24.74	27.81	26.22	28.43	28.0	25.98	27.23	32.46	32.64	34.38

Table III
Comparison with different Existing Methods for images(1-boat.jpg,2- Lena.jpg,3-pepper.jpg) using MSE values

ND	SMF			WMF			DBA			PA		
	1	2	3	1	2	3	1	2	3	1	2	3
10%	118.28	110.36	86.29	54.17	41.03	44.39	34.99	32.14	24.08	15.72	7.32	3.64
20%	149.09	142.04	124.45	74.38	56.51	65.44	52.41	48.48	39.21	18.24	10.29	5.46
30%	173.83	168.59	155.25	88.80	65.60	78.01	63.56	59.84	51.23	21.52	13.99	7.80
40%	193.60	189.59	178.45	96.90	70.15	85.05	73.22	69.58	61.99	24.84	18.54	11.43
50%	194.38	206.05	198.17	103.13	73.41	90.58	81.34	78.38	72.32	30.17	25.79	17.31
60%	209.21	218.30	211.96	107.52	75.12	93.28	89.18	87.23	80.58	36.82	35.33	23.68

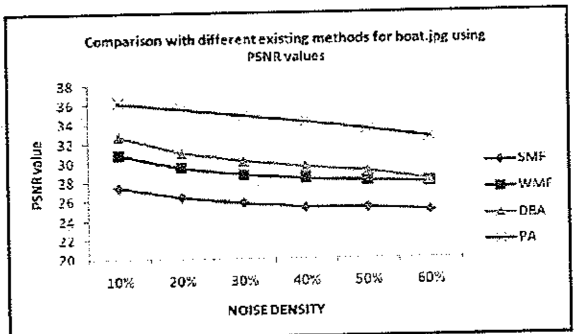

Figure 3 : Comparison with different existing methods

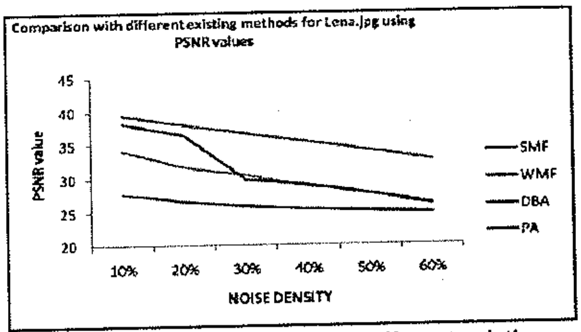

Figure 4 : Comparison with different existing methods

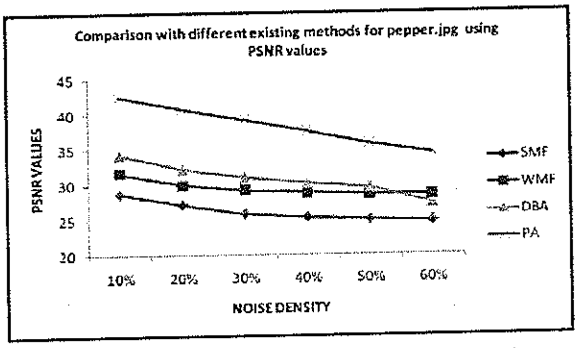

Figure 5 : Comparison with different existing methods PSNR values

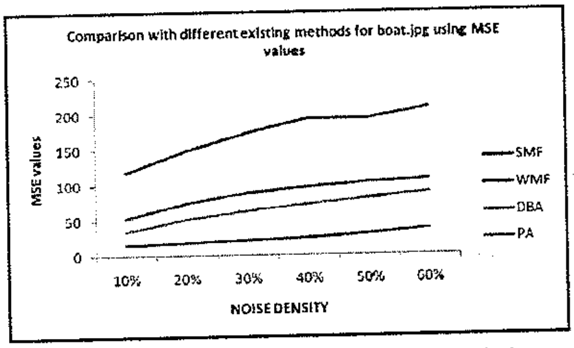

Figure 6 : Comparison with different existing methods PSNR values

VII. Conclusion

In noise detection the ROAD value can effectively differentiate between the impulse from edges and other fine features in the image. In noise estimation the robust estimation which can successfully handle intensity discontinuities performs well in predicting the accurate estimated value. The proposed method considers only 3x3 neighborhoods for noise detection and during the estimation phase the window size is extended in the absence of noise free pixel for estimation and so the computations are minimized. The maximum window size is 7X7 this avoids blurring of the restored image. The proposed method performs well at high noise density which is proved using visual analysis, PSNR values, and MSE values and by comparing with some of the existing methods. So, this method proves to be an efficient, high performing, preprocessing tool for images corrupted with impulse noise.

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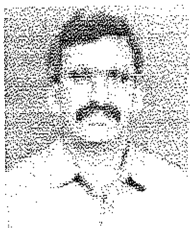

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