Color Image De-noising Using Fuzzy Peer Groups & Robust Estimation

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Abstract--An algorithm for de-noising fixed value impulse noise from color images is proposed. The peer group for every image pixel is constructed using fuzzy metrics on the fixed window size and is used for Noise detection. The corrupted pixels are identified and replaced by the estimated value by Lorentzian estimator. The noise free pixels remain un-altered .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.

***Keywords*— Fuzzy similarity, Fuzzy Peer Groups, 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. Noisy images can be found in many today's imaging applications. TV images are corrupted because of atmospheric interference and imperfections in the image reception. Noise is also introduced even in digital artworks when scanning damaged surfaces of the originals. Digital cameras may introduce noise because of CCD sensor malfunction, electronic interference or flaws in data transmission. 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.

De-noising impulse noise has been studied over decades and many filters have been proposed. In earlier days, linear filters [8] 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. SMFs often exhibit blurring at high noise densities, for all large window sizes and insufficient noise suppression for all small window sizes.

Weighted median filter(WMF) [1](Arce.G), RWM[2] filter are some improved versions of median filter. However, when the noise level is over 50%, some details and edges of the original image are smeared by the filter. 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. Different remedies of the median filter have been proposed, which are "decision-based" or "switching-based" filters[8][11][12] and they first identify possible noisy pixels and then replace them by using the median filter or its variants, while leaving all other pixels unchanged. These filters are good at detecting noise even at a high noise level. Without taking into account of local features such as the possible presence of edges, the noisy pixels are replaced by some median value in their vicinity. This was the main drawback of these filters. Hence details and edges are not recovered satisfactorily, especially when the noise level is high.

In this paper an efficient algorithm based on robust estimation is presented to remove salt and pepper noise effectively upto a noise density of 70%. The proposed algorithm uses simple fixed length window of size 3 x 3 for noise detection based on fuzzy peer groups, 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.

II. FUZZY PEER GROUPS

Fuzzy peer group of a pixel is actually the collection of pixels which have some common nature. Fuzzy Peer Groups are constructed based on the similarity between the pixels using its intensity values. Since the similarity between the image pixels cannot be expressed effectively in a crisp way a fuzzy approach is proposed[9] .

Let p be the image pixel under consideration. . Each pixel is represented as a 3-component vector comprising its R, G, and B components, i.e., $p_i=[p^{Ri},p^{Gi},p^{Bi}]$, where Ri, Gi, Bi are the red, green ,blue component of the i th pixel p_i , such that p_i ε W.

The fuzzy peer group FP(G) of p is the pixels in the window (3X3) is computed using the fuzzy similarity function . The similarity between the two color vectors A, B in the RGB space is given by

$$\rho(A,B)= \frac{1}{1+D(A,B)} \qquad (1)$$

Where D(A,B) is the Euclidean distance between A & B. The similarity value computed using the above equation is compared with the threshold value T which is computed based on Otsu's equation[7]. The set of pixels in W < T forms the fuzzy peer group for the corresponding image pixel.

III. 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 [5] as a generalization of the maximum likelihood estimator. The M estimator addresses the problem of finding best fit to the model={d0,d1,d2,...,dS-1} to another model. e={e0,e1,e2,...,eS-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 function.

$$\min_{s\in S} \sum \rho((es - ds),\sigma) \qquad (2)$$

where σ scale parameter that controls the outlier ejection 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. ds is the input model and es is the best fit model. To minimize above, it is necessary to solve the equation (3) & (4)

$$\sum \Psi((e_s - d_s),\sigma) = 0 \qquad (3)$$

where the influence function given by the equation (4),

$$\Psi(x,\sigma) = \frac{\partial \rho(x,\sigma)}{\partial x} \qquad (4)$$

Generally, Influence function and breakdown point are the two parameters used to measure the robustness. 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. Lorentzian estimator [3][4] is an Influence function which tends to zero for increasing estimation distance and maximum breakdown value.

The Lorentzian estimator ρLOR(x) is defined by the equation (5)

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

and it is described by the influence function ψLOR(x) given by the equation (6)

$$\psi\, LOR(x) = \rho' LOR(x) - \frac{2x}{2\sigma^2 + x^2} \qquad (6)$$

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

IV. PROPOSED ALGORITHM

This method uses ROADm 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.

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 Fuzzy peer group for the pixel is constructed using the fuzzy similarity function using the following steps
   a. Find the similarity measure between the central pixel and all the pixels in W in the RGB space.
   b. compare the similarity measure ρ with the local threshold valueT. If ρ >T, add the pixel in FP(G).
3. The pixel is detected whether impulse as

If n(FP(G)) >8
central_pixel= 'impulse'
else
centre_pixel= 'noise free'

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

Estimation phase

Lorentzian estimator is used for estimation. The estimation phase has the following steps[10]

1. Select the noise free neighborhood pixels. i.e the pixels within the range [0,255]
2. Find x , the difference of each selected pixel with the median value and compute the function f(x) given in the equation(7)

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

Where σ is outlier rejection point, given by the equation (8),

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

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

$$T_s = \zeta\sigma N \quad (9)$$

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.

3. Pixel is estimated using the equations (10) and (11)

$$S_1 = \sum_{l \in L} \frac{pixel(l) * f(x)}{x} \quad (10)$$

$$S_2 = \sum_{l \in L} \frac{f(x)}{x} \quad (11)$$

Where L is number of selected pixels in the window.

4. Ratio of S_1 and S_2 gives the estimated pixel value which replaces the impulse pixel.
5. Repeat the steps 1 through 4 separately for the three color components of the image.

V. PERFORMANCE EVALUATION

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

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 (12).

$$MSE = \frac{1}{MN} \sum_{y=1}^{M} \sum_{x=1}^{N} [I(x,y) - I'(x,y)]^2 \quad (12)$$

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.

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 (13)

$$PSNR = 10\log 10\left(\frac{255^2}{MSE}\right) \quad (13)$$

Where MSE is given by equation (12)

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 the two standard images Lena.jpg and peppers. 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 values decreases. But from the consistent results on different images it is proved that the method holds well for different images with different characteristics. The visual results in Fig. 3 & 4 shows that the method is good in retaining edges, avoids blurring and removing noise. So it is proved that the proposed algorithm is good in preserving image details, has high PSNR, low MSE values and performs effectively to de-noise color images.

TABLE I

PERFORMANCE OF THE ALGORITHM WITH THREE DIFFERENT COLOR IMAGES (512 X 512)

Noise Density	MSE Values		PSNR Values (db)	
	Lena.jpg	Peppers.jpg	Lena.jpg	Peppers.jpg
0%	6.2130	6.2538	40.1978	40.1694
10%	10.3010	7.7814	38.0020	39.2202

20%	12.3570	10.1580	37.2117	38.0627
30%	15.8828	14.4612	36.1215	36.5288
40%	21.9206	21.1182	34.7223	34.8842
50%	31.9015	31.4456	33.0927	33.1552
60%	46.5109	46.4408	31.4553	31.4618
70%	61.6721	65.3366	30.2299	29.9792

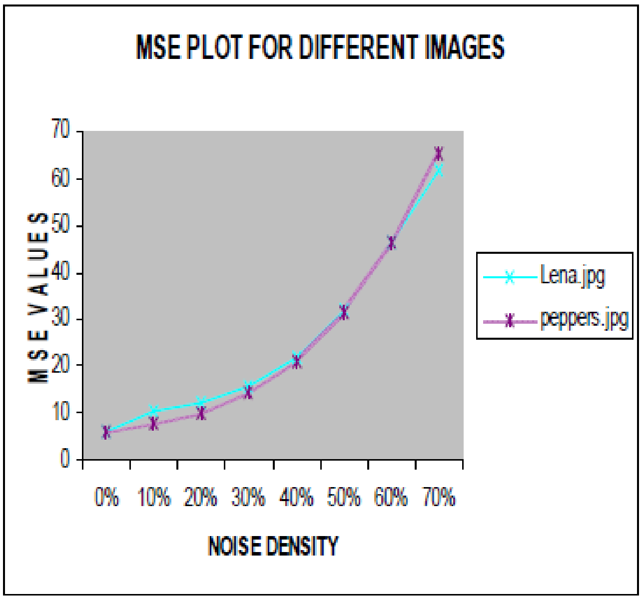

Fig.1 MSE Plot for different images

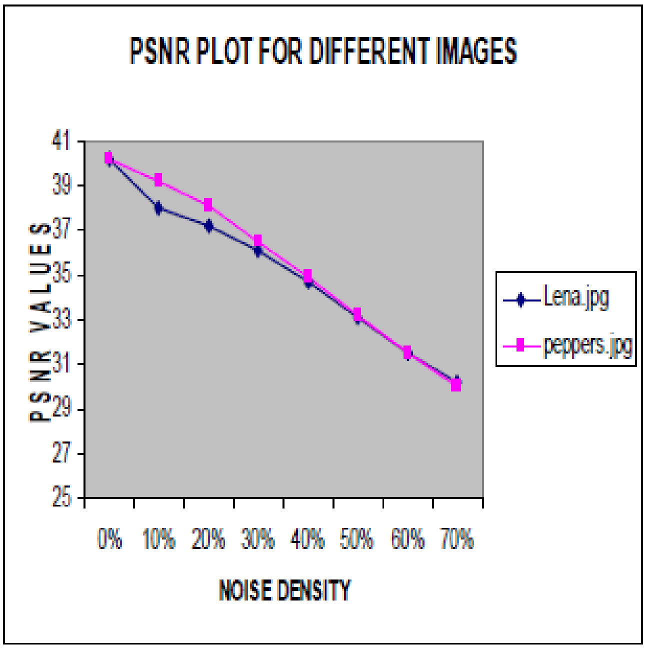

Fig.2 PSNR Plot for different images

Fig. 3 Simulation results using Lena.jpg. (a) Original image. (b) Noisy image (60%). (c)Output using the proposed method for noise density 60% (d) Noisy image (70%). (e) Output using the proposed method for noise density 70%.

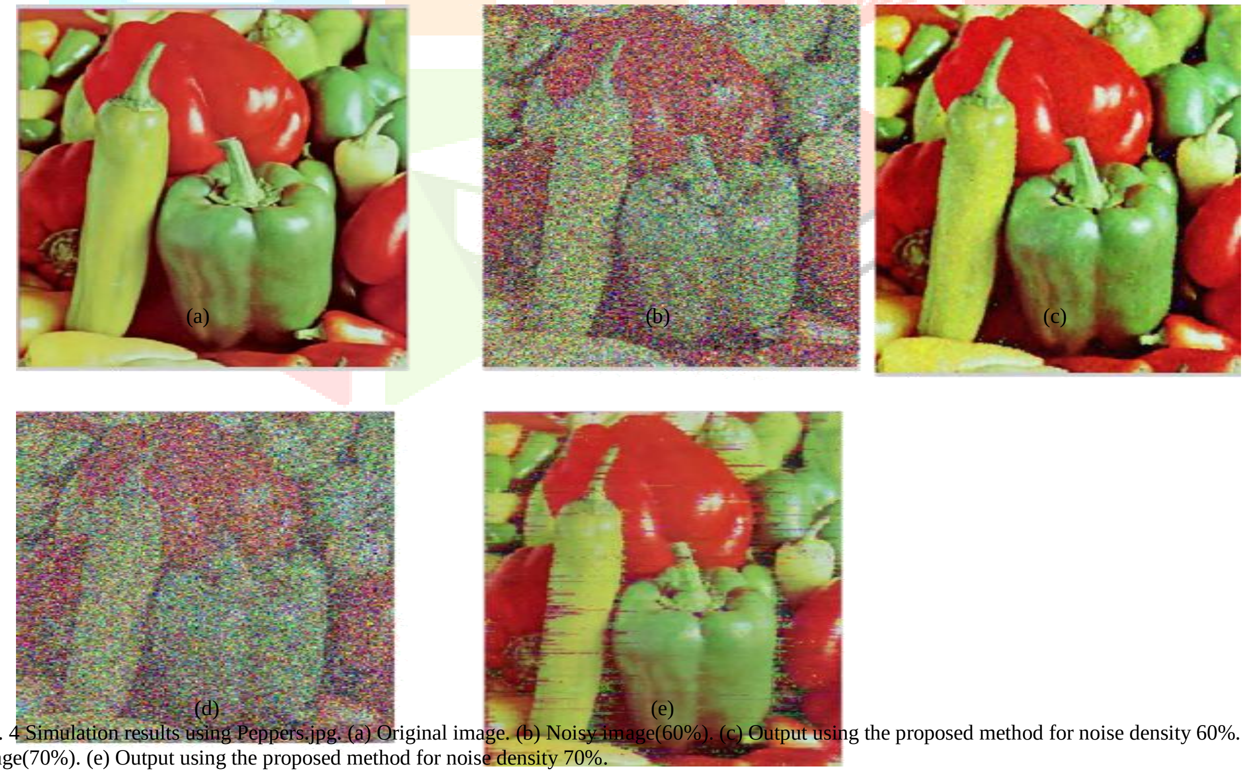

Fig. 4 Simulation results using Peppers.jpg. (a) Original image. (b) Noisy image(60%). (c) Output using the proposed method for noise density 60%. (d)Noisy image(70%). (e) Output using the proposed method for noise density 70%.

VI. Conclusion

In noise detection the fuzzy peer groups 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 so the computations are minimized and this avoids blurring of the restored image. The proposed method performs well at high noise density which is proved using visual analysis, PSNR values, MSE values and by comparing with some of the existing methods. So, this method proves to be an efficient, high performing, preprocessing tool for color images corrupted with impulse noise.

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