

Fuzzy Entropy based Impulse Noise Detection and Correction Method for Digital Images

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Abstract—Impulse noise is the prime factor which reduces the quality of the digital image and it erases the important details of the images. De-noising is an indispensable task to restore the image features from the corrupted low- quality images and improve the perceptual quality of images. Several techniques are used for image quality enhancement and image restoration. In this work, an image de-noising scheme is developed to detect and correct the impulse noise from the image by using fuzzy entropy. The proposed algorithm is designed in two phases, such as noise detection phase, and correction phase. In the noise detection phase, the fuzzy entropy of pixels in a window of interest (WoI) is computed to detect whether the pixel is noisy or not. The Fuzzy entropy of pixel greater than specified alpha cut value will be considered as noise pixel and submitted to correction phase. In the correction phase noise pixel value is replaced with a fuzzy weighted mean of the uncorrupted pixels in the WoI. The proposed Fuzzy entropy based impulse noise detection and correction method are implemented using MATLAB. The experimentation has been carried out on different standard images and the analysis is performed by comparing the performance of the proposed scheme with that of the existing methods such as DBA, MDBUTMF, AMF, NAFSM, BDND, and CM, using PSNR, SSIM, and NAE as metric parameters. The proposed method will give good results compared to state of the art methods in image restoration.

Index Terms—Fuzzy entropy, a window of interest, impulse noise, image restoration.

I. INTRODUCTION

With the advent and usage of multimedia, visual data from quality digital images play a significant role in human day to day life applications. Unfortunately, images which are captured through many cameras have been generally subjected to the contamination of impulse noise. Generally impulse noise caused by malfunctioning pixel sensors, defective memory units, and imperfections

encountered in a channel for the duration of transmission and timing errors in analog-to-digital conversion [1-4]. Before successive digital image processing operations, restoring of the corrupted image has been accomplished as the first step in digital image processing.

Image restoration is imperative for successive tasks (e.g., edge detection, image segmentation, classification, parameter estimation, etc.) which are basically affected by the quality of the image. Capturing devices has become sensitive to the acquaintance of impulse noise due to more sensing elements per unit space are integrated on a single chip. To overcome this, digital camera manufacturing companies rely on restoration methods to enhance the visual quality of the image acquired. As a result, a number of methods have been proposed for the removal of impulse noise. Non-linear filters are superior to linear filter with their great execution to restoring the image from impulse noise, For instance, the median filter [2],[5] could be a natural selection for suppressing impulse noise. The idea of a median filter is to replace the window pixel given by the median of the brightness in the window. The Median filter gives the better results at low noise levels (<10%)[12] but it alters the image pixels even though it is not corrupted, this led to bad result at high noise levels (>10%)[12], the key image details are also decorated. This problem has led to the development of various classes of filters, such as the weighted median-filters [1], [2], [4]-[7], [9], adaptive filters [8],[12], and rank-ordered statistics, switching median filter and soft computing filters [9-14],[16], [28-29].By adapting these non-linear filters, the restoration quality Significantly increases but the implementation and time complexity is multiplied and hardware cost also increases. In this paper, we propose a new filtering mechanism is proposed for high impulse noise removal with less computational cost using fuzzy entropy. The proposed technique restored the digital image with less computational time and it simultaneously maintaining edge information compare with different existing filters.

II. IMPULSE NOISE MODELS

In this section, impulse noise models are clearly described. A digital image of size $R \times C$ stored as an 8-bit gray level image and the image elements are lie in the range $[0,255]$. In this, least and highest intensity values are 0 and 255. Regardless of its origin, impulse noise shows non stationary measurable qualities [1], [3] and just a specific percentage of pixels in the digital images are corrupted by impulse noise [12]. In view of this reality, the models for impulse noise with probability P defined in[12] as

$$SNP_Image(i, j) = \begin{cases} \frac{P}{2}, & \text{for } In_Image(i, j) = 0 \\ 1 - P, & \text{for } In_Image(i, j) \\ \frac{P}{2}, & \text{for } In_Image(i, j) = 255 \end{cases} \quad (1)$$

where the P is the noise probability density

Noise Model-I

$$SNP_Image(i, j) = \begin{cases} P_1, & \text{for } In_Image(i, j) = 0 \\ 1 - P, & \text{for } In_Image(i, j) \\ P_2, & \text{for } In_Image(i, j) = 255 \end{cases} \quad (2)$$

where the P is the noise probability density $P=P_1+P_2$ and $P_1 \neq P_2$

Noise Model-II

In the literature, usually two impulse noise models: salt-and-pepper (SNP) noise and random-valued impulse noise. Which are used as a part of image processing. In the SNP noise the image intensity values are set to be 255(salt) that is all the bits in gray level set to be one and 0(pepper) that is all the bits in gray level set to be zeros. In random-valued impulse noise model, the image intensity values are set to be any value within the dynamic range $[0,255]$. In the real world scenario, impulse noise is generated from the overlapping of impulse noise signals with random amplitudes. As a result, the impulsive amplitude could both fall within the image dynamic range or out of that range. While the impulsive amplitude lies outside of the dynamic range, the resultant pixel might be saturated and threshold to the 255 or 0 intensity value of the image and looks as SNP noise. On the other hand, if the impulsive amplitude lies in the dynamic range, the resultant pixel seems as uniform noise (UNIF) noise within the image.

The noise model-I is SNP model with equal probability as represented in equation-1 and Noise Model II is similar to model-II, except that salt noise and pepper noise are with unequal probability as represented in equation-2.

$$Unif_Image(i, j) = \begin{cases} \frac{P}{2M}, & \text{for } 0 \leq In_Image(i, j) < M \\ 1 - P, & \text{for } In_Image(i, j) \\ \frac{P}{2M}, & \text{for } 255 - M < In_Image(i, j) \leq 255 \end{cases} \quad (3)$$

where the P is the noise probability density

Noise Model-III

$$Unif_Image(i, j) = \begin{cases} \frac{P_1}{M}, & \text{for } 0 \leq In_Image(i, j) < M \\ 1 - P, & \text{for } In_Image(i, j) \\ \frac{P_2}{M}, & \text{for } 255 - M < In_Image(i, j) \leq 255 \end{cases} \quad (4)$$

where the P is the noise probability density $P=P_1+P_2$ and $P_1 \neq P_2$

Noise Model-IV

The noise model-III is UNIF model with equal probability as represented in equation-3 and Noise Model IV is similar to model III, except that salt noise and pepper noise are with unequal probability as represented in equation-4.

III. FUZZY ENTROPY MEASURE FOR IMPULSE NOISE IDENTIFICATIONS

An image X of size $R \times C$ having L gray levels ranging from L_{\min} to L_{\max} can be defined as an array of fuzzy singletons .Each element in the array is the membership function value representing its degree of brightness relative to gray level l ($l = L_{\min}, L_{\min} + 1, \dots, L_{\max}$). Therefore, in fuzzy set notation, we can write

$$X = \{\mu p(i, j) / p(i, j), i = 1, 2, 3, 4, \dots, R; j = 1, 2, 3, 4, \dots, C\} \quad (5)$$

$$\mu p(i, j) = e^{-\frac{(p(i, j) - \bar{P})^2}{2\sigma^2}} \quad (6)$$

Where

$$\sigma = \sqrt{\frac{\pi}{2}} \times \frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n |p(i, j) - \bar{P}| \quad (7)$$

Where

$$\bar{P} = \frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n p(i, j) \quad (8)$$

From the entropy concept, we know that fuzzy entropy [17-22],[27] is less for orderly image pixel values and more for disorderly image pixels. If we try to visualize the image data, information pixels are orderly configured and impulse noise pixels are disorderly configured. So if we evaluate the fuzzy entropy at each image pixel then the image pixel with minimum fuzzy entropy is an informative pixel and with higher fuzzy entropy is an impulse noise pixel.

The fuzzy entropy value of pixel in given a window of interest can be calculated as given in equation-5

$$E(\mu(p_i)) = -\mu(p_i) \log_2 \mu(p_i) - (1 - \mu(p_i)) \log_2 (1 - \mu(p_i)), 0 \leq \mu(p_i) \leq 1 \quad (9)$$

The fuzzy entropy value of the image pixels in the given window is in the range [0.0-1.0]. Fuzzy Entropy Value is low for the pixel, which lie between 0 and 255 and very high (close to 1) for the 0 and 255. Fuzzy entropy assumes the maximum value of 1.0 when $\mu(p_{(i,j)})$ is 0.5 and a minimum value of 0.0 when $\mu(p_{(i,j)})$ is 0.0 or 1.0 [22].

IV. IMPULSE NOISE DETECTION METHOD USING FUZZY ENTROPY MEASURE

This section describes the Fuzzy Entropy Based Impulse Noise Detection (FEIND) algorithm and then discusses the some of the implementation issues of the algorithm. The algorithm-I is used to detect the pixel is impulsive or not with fuzzy entropy. The basic working principle of an algorithm-I is that, given image convert into the fuzzy plane using the Gaussian membership function, then compute the fuzzy entropy of image pixels using the equation-5.

A greater difference of the values among the evaluation pixels results in a higher fuzzy entropy and pixel values which are similar in the window results in lower fuzzy entropy. Using this underlying idea the pixels can be classified as corrupted or uncorrupted. To identify given pixel in the window of interest (WoI) is impulsive or not, calculate the fuzzy entropy of processing pixel in the WoI and check whether the fuzzy entropy of pixel is greater than the given alpha cut value. If it is greater than the given alpha cut value then it is impulsive and submitted to correction phase. Skelton of the noise detection is given in algorithm-I.

A. Impulse Noise Detection Method Using Fuzzy Entropy Measure

FEIND method keeps its original value as it is in the processed image if it detects the pixel values is informative. Only impulse noise pixels are submitted to correction phase, which is similar to traditional switching filters. Traditional switching filters first identify the noise pixels and form the binary noise map of the image to record the information of impulse noise such as noise pixel location. Fuzzy weighted mean filter corrects the noise pixel one after another using the information in noise map and it leads to increase of CPU time and require more main memory space. To overcome this drawback, the FEIND filter corrects the impulse noise immediately after the pixel has been detected as an impulsive candidate. Hence, in the FEIND filter, for the

noise detection and the correction use the same window of interest. The details are shown in the algorithm-I.

V. RESULTS AND DISCUSSIONS

In this section, from the experimental study we are going to address the following two points:

1. FEIND method can identify the impulse noise pixels in given image
2. Restore the corrupted pixel value with the fuzzy mean of uncorrupted pixels in WoI.

In order to accomplish the tasks, we use Lena, Parrot, and bridge corrupted mages with impulse noise model-I, noise density range from 30% to 90%. To show FEIND is able to detect the impulse noise candidate, we experimented with different window size on various noise levels by choosing the different alpha cut values range from 0.1 to 0.9. The Fig.1 Depicts the input 7x7 image with 70% of impulse noise and Figure.2 represent the fuzzy entropy of the corrupted image. From the Table-I we can conclude that the pixels with intensities 0 and 255 having greater fuzzy entropy than the remaining pixels. The pixel is treated as a noise pixel if it having greater fuzzy entropy than the specified alpha cut value and it is submitted to next filtering stage. Otherwise, the pixel is treated as informative pixel and it keeps as it is in the processed image. Table IV, Table V, Table VI and Table VII lists the accuracies of identification of the noise pixels with various window sizes, which are defined using two factors. One is the number of missed detections (MD), namely, the number of noise pixels that are identified as uncorrupted pixels. The other one is the number of false alarms (FA), i.e., the number of uncorrupted pixels that are identified as noise pixels [12]. Among the filtering windows, the 7x7 has less MD and

Algorithm-I

For every pixel $p_{i,j}$ image do

1. Get region R for image pixel $p_{i,j}$ by taking $M=4$

$$P_{i,j}^M = \{p_{i+a,j+b} | M \geq a,b \geq 0\}$$
2. Calculate the sample mean of the Region p, i.e.,

$$\bar{p} = \frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n p(i,j)$$

3. Calculate the Standard Deviation of the Region p, i.e.,

$$\sigma = \sqrt{\frac{\pi}{2} \times \frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n |p(i,j) - \bar{p}|}$$

4. Calculate the fuzzy membership of the processing pixel $p_{i,j}$, i.e.,

$$\mu(p_{i,j}) = e^{-\frac{(p_{i,j} - \bar{p})^2}{2\sigma^2}}$$

5. Calculate the fuzzy entropy of the processing pixel $p_{i,j}$, i.e.,

$$E(\mu(p_{i,j})) = -\mu(p_{i,j}) \log_2 \mu(p_{i,j}) - (1 - \mu(p_{i,j})) \log_2 (1 - \mu(p_{i,j})), 0 \leq \mu(p_{i,j}) \leq 1$$

6. if $E(\mu(p_{i,j})) < T$ then

$$p_{i,j} = \bar{p}_{i,j}, \text{continue}$$
7. else
8. $p_{i,j}$ is corrupted with impulse noise

Algorithm-II

1. Calculate the sample mean of the pixels in the Region p, i.e.,

$$\bar{p} = \frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n p(i,j)$$

2. Calculate the Standard Deviation i.e.,

$$\sigma = \sqrt{\frac{\pi}{2} \times \frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n |p(i,j) - \bar{p}|^2}$$

3. Calculate the fuzzy membership of the pixels in t p_{i,j}, i.e.,

$$\mu_F(p_i) = e^{-\frac{(p_{i,j} - \bar{p})^2}{2\sigma^2}}$$

4. Calculate the fuzzy entropy of the processing pixel p_{i,j}, i.e.,

$$E(\mu(p_{i,j})) = -\mu(p_{i,j}) \log_2 \mu(p_{i,j}) - (1 - \mu(p_{i,j})) \log_2 (1 - \mu(p_{i,j})), 0 \leq \mu(p_{i,j}) \leq 1$$

5. if E(μ(p_{i,j})) < T then

$$\text{fuzzy weights of uncorrupted pixel is } w_i = \mu(p_{i,j}) = e^{-\frac{(p_{i,j} - \bar{p})^2}{2\sigma^2}}$$

6. compute the fuzzy weighted mean of uncorrupted pixel, i.e.,

$$y_{i,j} = \sum_{i=1}^n p_i^* \mu(p_i)$$

where n = number of un-corrupted pixels in the region of interest

FA (see Table-III&VIII) at the alpha cut value in between 0.5 to 0.6. Therefore, image restoration using 7x7 window gives the better visual quality than the remaining windows. All the windows up to 0.4 alpha cut value gives the zero false alarms but gives more missed detections. For the 60% and 80% impulse noise, the window size 5x5 with alpha cut vale 0.6 gives the least missed detection and zero false alarms. The window size 7x7 with alpha cut vale 0.5 gives the least missed detections and zero false alarms for the noise densities range from 30 to 90. The window size 9x9 with alpha cut value 0.6 gives the least missed detections and zero false alarms for the noise density 60% and gives the zero missed detection and least false alarms for the noise density 70%. From the Tables IV to VII finally concluded that the alpha cut value between 0.5 to 0.6 with window size 7x7 gives least missed detections and false alarms. Table-IX shows the identification time required to classify the noisy pixel and information pixel using various windows. From the above analysis we concluded that the window size 5x5 gives least computational time and 11x11 gives the more computational time. From the table-VII, For the 90% of impulse noise with Window size 7x7 and alpha cut value 0.5100 gives zero MD and zero FA. For the 80% of impulse noise with Window size 7x7 and alpha cut value 0.5500 gives zero MD and zero FA. For the 70% of impulse noise with Window size 7x7 and alpha cut value 0.5980 gives zero MD and zero FA. For the 60% of impulse noise with Window size 7x7 and alpha cut value 0.5996 gives zero MD and zero FA. For the 50% of impulse noise with Window size 7x7 and alpha cut value 0.5768 gives zero MD and zero FA. Table-IV describes the Computational require to classify the pixel with various window sizes 5X5 to 11X11.

$$P_{7 \times 7} = \begin{bmatrix} 255 & 0 & 0 & 126 & 108 & 105 & 0 \\ 125 & 0 & 0 & 255 & 107 & 0 & 255 \\ 255 & 124 & 186 & 138 & 0 & 255 & 255 \\ 135 & 0 & 0 & 255 & 255 & 0 & 255 \\ 0 & 0 & 255 & 0 & 150 & 255 & 152 \\ 0 & 255 & 255 & 255 & 255 & 255 & 0 \\ 0 & 255 & 255 & 255 & 255 & 0 & 127 \end{bmatrix}$$

Fig.1. Input 7x7 image corrupted with 70 % of salt and pepper noise.

Table 1. Fuzzy entropy of the each pixel

Gray value	Fuzzy entropy
0	0.9924
126	0.0332
108	0.1711
105	0.1996
125	0.0387
107	0.1804
124	0.0446
186	0.3870
138	0.0012
135	0.0010
150	0.0523
152	0.0656
127	0.0279
255	0.9447

From that, window size 7x7 requires average less computational time to classify the pixels with the noise density ranges from 30% to 90%.

Restoration performance of proposed method implemented using standard gray scale images of size 256x256 with 8-bit resolution. Each of the test images is degraded with Noise Model-I and noise density ranging from 10 % to 90 % in 10% noise step. For comparison, degraded images also restored using the existing filters adaptive median filter (AM), Decision-Based algorithm for Impulse Noise Removal (DBA) [13], DBUTMF [14], NAFSM [11], boundary discriminative noise detection (BDND) [12] and cloud model filter (CM) [16]. AM utilizes the adaptive window mechanism for recognizing.

Corrupted and uncorrupted pixels, next to the filtering approach, was applied, for AMF initial window size is 3x3 consider and incrementing the window size maximum to 39 with 2 in step.

The DBA is implemented with the 3x3 window, it removes only corrupted pixel by the median value of its neighboring pixels. For the BDND in the first iteration, the window size 21x21 is used, if it fails to find the impulse noise, conditionally invokes the second iteration with window size 3x3 Initial window size of 3x3 to maximum window size of 13x13 with 2 step increment is used to implement the CM. For the FEIND filter window of interest, 7x7 is used for pixel classification.

Table I & II are show the restoration results of the Lena image corrupted with noise density range from

30 % of impulse noise to 80% impulse noise in terms of PSNR, [27] and NAE. The table values show that the proposed method gives good performance compare to existing filters. In other two images house and parrot the proposed method gives the better results compare to AM, DBA, MDBUTMF and NASFM and gives average performance compare to BDND and CM filters. Fig.3.a shows original Lena and parrot images, Fig.3.b represents the images corrupted with 30% impulse noise, Fig.3.c represent the noise image with 60 % impulse noise and Fig.3.d represents the noise images with 80% impulse noise.

Fig.4 to Fig.8 illustrate the visual quality of the restored images of filters DBA, DBUTM, AMF, NAFSM,

BDND, CM and proposed method. Fig. 4 and Fig.8 conclude that all the filters exhibit almost similar visual quality at 30% noise level, from the Fig.5 and Fig.8 we conclude that the visual quality of the DBA method is poor at noise level 60%, and proposed method provides the better visual quality compared to remaining state of art algorithms. From the Fig.6 and Fig.9, we conclude that the DBA, MDBUTMF and AMF filters provide the poor visual quality at noise level 80% and NAFSM, BDND methods provide better visual quality compare to DBA, DBUTMF and AMF filters, CM and proposed methods give best visual quality compared to remaining all the methods.

Table 2. Comparison of Noise Detection Accuracy in MD And FA In 5x5 For Lena Image at Various Alpha Cut Values

Alpha cut values	Noise %													
	30		40		50		60		70		80		90	
	MD	FA	MD	FA	MD	FA	MD	FA	MD	FA	MD	FA	MD	FA
0.2	22494	0	19642	0	16010	0	13004	0	10054	0	6538	0	6099	0
0.3	13257	0	11988	0	10853	0	9033	0	7345	0	4686	0	5899	0
0.4	6575	0	6415	0	6284	0	5751	0	4919	0	3197	0	5677	0
0.5	747	0	1379	0	2283	0	2587	0	488	0	1379	0	397	0
0.6	0	5458	0	3556	0	1178	46	0	465	0	45	0	0	869
0.7	0	8177	0	5991	0	3045	0	1654	0	889	0	2044	0	5121
0.8	0	7908	0	7871	0	5471	0	3574	0	4518	0	9435	0	17382
0.9	0	9795	0	12470	0	11247	0	11457	0	15818	0	24333	0	35975

Table 3. Comparison of Noise Detection Accuracy in MD and FA in 7x7 For Lena Image at Various Alpha Cut Values

Alpha cut values	Noise %													
	30		40		50		60		70		80		90	
	MD	FA	MD	FA	MD	FA	MD	FA	MD	FA	MD	FA	MD	FA
0.2	20201	0	18492	0	15545	0	12237	0	9730	0	6274	0	3177	0
0.3	11787	0	11912	0	10782	0	8886	0	6853	0	4508	0	2268	0
0.4	4855	0	6194	0	5917	0	5577	0	4701	0	3172	0	1621	0
0.5	0	923	778	0	635	0	376	0	149	0	68	0	71	0
0.6	0	5744	0	3122	0	523	0	36	243	0	0	422	0	893
0.7	0	9004	0	5685	0	698	0	1400	0	846	0	1528	0	2310
0.8	0	11693	0	9026	0	2986	0	2849	0	2674	0	5208	0	11815
0.9	0	14098	0	13745	0	9894	0	8578	0	11038	0	20988	0	35156

Table 4. CPU Time In Seconds For Bridge Image

WINDOWS	Noise %							
	30	40	50	60	70	80	90	
5X5	2.148925	2.098575	2.167425	2.109863	2.108038	2.10855	2.118725	
7X7	2.913102	2.874481	3.068724	2.937363	2.769388	2.8508	3.025413	
9X9	3.682938	4.454363	4.9594	3.807875	3.887388	4.046488	4.0685	
11X11	5.373723	5.495475	6.081713	5.474063	7.592563	5.72225	5.30525	

Table 5. Comparison of Noise Detection Accuracy In MD and FA in 9x9 For Lena Image at Various Alpha Cut Values

Alpha cut values	Noise %													
	30		40		50		60		70		80		90	
	MD	FA	MD	FA	MD	FA	MD	FA	MD	FA	MD	FA	MD	FA
0.2	20761	0	18408	0	15555	0	12265	0	9639	0	6257	0	3066	0
0.3	12907	0	12525	0	11189	0	8947	0	7066	0	4635	0	2256	0
0.4	5629	0	7159	0	7323	0	5581	0	4789	0	3144	0	1587	0
0.5	0	502	2065	0	3222	0	2384	0	1793	0	698	0	0	87
0.6	0	5358	0	2972	6969	0	29	0	0	52	0	1002	0	1383
0.7	0	8985	0	5872	0	125	0	1079	0	1094	0	1768	0	2227
0.8	0	12073	0	9946	0	5110	0	2280	0	1953	0	4220	0	8478
0.9	0	14416	0	14757	0	10463	0	7639	0	9077	0	18469	0	34910

Table 6. Comparison of Noise Detection Accuracy In MD And FA in 11x11 For Lena Image at Various Alpha Cut Values

Alpha cut values	Noise %													
	30		40		50		60		70		80		90	
	MD	FA	MD	FA	MD	FA	MD	FA	MD	FA	MD	FA	MD	FA
0.2	21159	0	19964	0	16032	0	12477	0	9746	0	6178	0	3123	0
0.3	13756	0	13377	0	11785	0	9335	0	7191	0	4415	0	2476	0
0.4	6950	0	7649	0	7440	0	6290	0	5007	0	3378	0	1706	0
0.5	304	0	2685	0	3284	0	2149	0	1851	0	597	0	0	444
0.6	0	4655	0	1617	307	0	0	45	0	470	0	1155	0	1979
0.7	0	8750	0	6253	0	2026	0	1199	0	1649	0	2212	0	2741
0.8	0	11880	0	9876	0	4302	0	2126	0	2221	0	3727	0	7034
0.9	0	14383	0	14980	0	9970	0	7089	0	8364	0	17177	0	35381

Table 7. Comparison Of Zero MD and FA For Lena Image At Different Alpha Cut Values For Various Noise Densities With Window Size 7x7

Alpha cut values	Noise %									
	50		60		70		80		90	
	MD	FA	MD	FA	MD	FA	MD	FA	MD	FA
0.5100	--	--	--	--	--	--	--	--	0	0
0.5500	--	--	--	--	--	--	0	0	--	--
0.5980	--	--	--	--	0	0	--	--	--	--
0.5996	--	--	0	0	--	--	--	--	--	--
0.5768	0	0	--	--	--	--	--	--	--	--

Table 8. Comparison of Noise Detection Accuracy In MD And FA in 7x7 For Bridge Image At Various Alpha Cut Values

Alpha cut values	Noise %													
	30		40		50		60		70		80		90	
	MD	FA	MD	FA	MD	FA	MD	FA	MD	FA	MD	FA	MD	FA
0.2	25078	0	21744	0	17911	0	14207	0	10735	0	7027	0	3608	0
0.3	18439	0	15892	0	13261	0	14608	0	7878	0	5209	0	2706	0
0.4	11843	0	10716	0	9233	0	7239	0	5543	0	3642	0	1888	0
0.5	88	0	24	0	61	0	153	0	174	0	241	0	507	0
0.6	0	37	0	09	0	83	0	144	0	172	0	149	0	937
0.7	0	5275	0	3885	0	1334	0	818	0	842	0	1254	0	2393
0.8	0	8842	0	7467	0	4971	0	3036	0	3825	0	5897	0	12464
0.9	0	12925	0	12439	0	9944	0	8745	0	12203	0	22636	0	36144

Table 9. Comparison Of Restoration Results For 'Leena' Test Image In Psnr (Db) And NAE

Methods	PSNR(dB)					NAE				
	30%	40%	50%	60%	80%	20%	40%	50%	60%	80%
AM	35.6125	33.6430	32.6876	30.7285	28.8328	0.82253	0.81653	0.7184	0.7119	0.6103
DBA	28.8834	18.8552	15.5678	12.2098	8.1785	0.9375	0.9225	0.9115	0.8618	0.6919
MDBUTMF	34.2395	30.2826	28.5198	26.1650	19.3849	0.9689	0.9243	0.8864	0.8093	0.4187
NAFSM	28.5933	23.6392	22.5576	21.5733	18.9354	0.8467	0.8258	0.7023	0.7047	0.6987
BDND	36.6334	33.6543	30.9698	28.2745	24.6634	0.9748	0.9601	0.9466	0.9345	0.8663
CM	38.4832	34.2883	32.5209	30.8287	27.6889	0.9732	0.9510	0.9498	0.9137	0.8789
PROPOSED	39.2674	36.0177	33.4274	32.7657	29.2326	0.9848	0.9610	0.9510	0.9232	0.8879

Table 10. Comparison Of Restoration Results For 'House' Test Image In PSNR (Db) and NAE

Methods	PSNR(dB)					NAE				
	30%	40%	50%	60%	80%	20%	40%	50%	60%	80%
AM	32.1074	30.1365	28.1808	27.1863	26.5904	0.8234	0.7199	0.6108	0.6042	0.5842
DBA	26.8497	18.1944	15.0307	12.2714	8.14053	0.8057	0.6107	0.5225	0.5052	0.4287
MDBUTMF	39.0911	34.2661	32.0790	28.7031	20.2540	0.9669	0.9242	0.8851	0.7933	0.3729
NAFSM	26.2650	26.4591	26.5212	26.7030	27.2948	0.7705	0.6990	0.5558	0.5056	0.4014
BDND	39.9874	37.1459	35.8447	32.9685	30.5698	0.9789	0.9698	0.9124	0.87495	0.8024
CM	40.8965	38.3698	36.4589	33.4478	32.4521	0.9801	0.9756	0.9678	0.95123	0.8147
PROPOSED	38.9439	35.0503	33.2855	31.5900	27.5910	0.9876	0.9742	0.9601	0.95295	0.8265

Table 11. Comparison Of Restoration Results For ‘Parrot’ Test Image In Psnr (Db) And Mae

Methods	PSNR					SSIM				
	30%	40%	50%	60%	80%	20%	40%	50%	60%	80%
AM	32.4287	36.4892	30.4763	27.4998	25.7119	0.1317	0.1284	0.1210	0.1243	0.1124
DBA	25.7226	17.8397	14.2937	11.7089	7.53686	0.7705	0.4431	0.2428	0.1325	0.0343
MDBUTMF	34.5077	29.6318	27.2146	24.3617	17.2021	0.9577	0.8995	0.8418	0.7469	0.3360
NAFSM	25.3554	25.4609	25.4866	25.7657	26.6167	0.3527	0.3520	0.3527	0.3510	0.3269
BDND	36.2255	34.1117	30.4456	28.9633	26.1123	0.9654	0.8963	0.8678	0.7891	0.5669
CM	38.2566	36.1996	33.7789	32.1455	30.7788	0.9755	0.9214	0.9012	0.8852	0.7960
PROPOSED	34.9120	31.0264	29.7323	28.3504	24.7187	0.9624	0.9188	0.8932	0.8624	0.7733

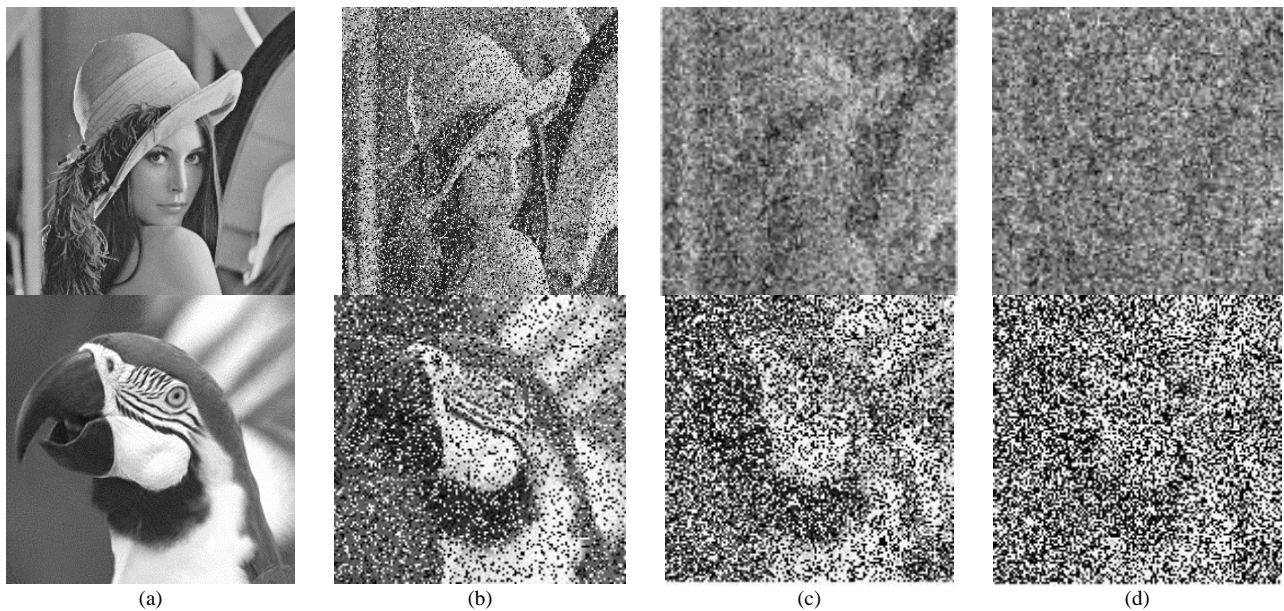


Fig.3.a) Original images b)Images corrupted with 30% noise c) Images corrupted with 60% noise d) Images corrupted with 80% noise



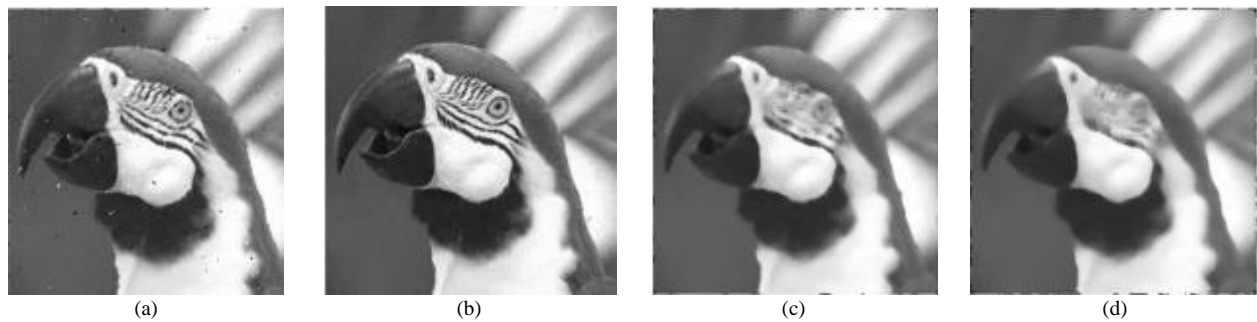
Fig.4. Results of denoising corrupted image “Lena,” with 30% impulse noise density (a)DBA (b)MDBUTMF (c)AMF(d)NAFSM(e)BDND(f)CM And (g)FEIND



Fig.5. Results of denoising corrupted image "Lena," with 60% impulse noise density (a) DBA (b) MDBUTMF (c) AMF (d) NAFSM (e) BDND (f) CM and (g) FEIND



Fig.6. Results of denoising corrupted image "Lena," with 80% impulse noise density (a) DBA (b) MDBUTMF (c) AMF (d) NAFSM (e) BDND (f) CM and (g) FEIND



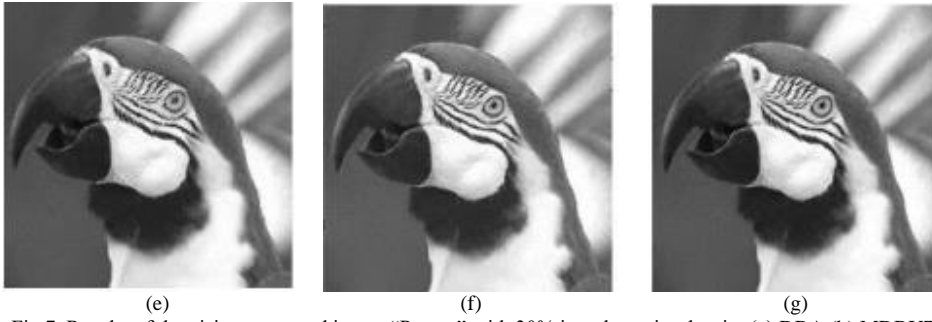


Fig.7. Results of denoising corrupted image “Parrot,” with 30% impulse noise density (a) DBA (b) MDBUTMF (c) AMF (d) NAFSM (e) BDND (f) CM and (g) FEIND

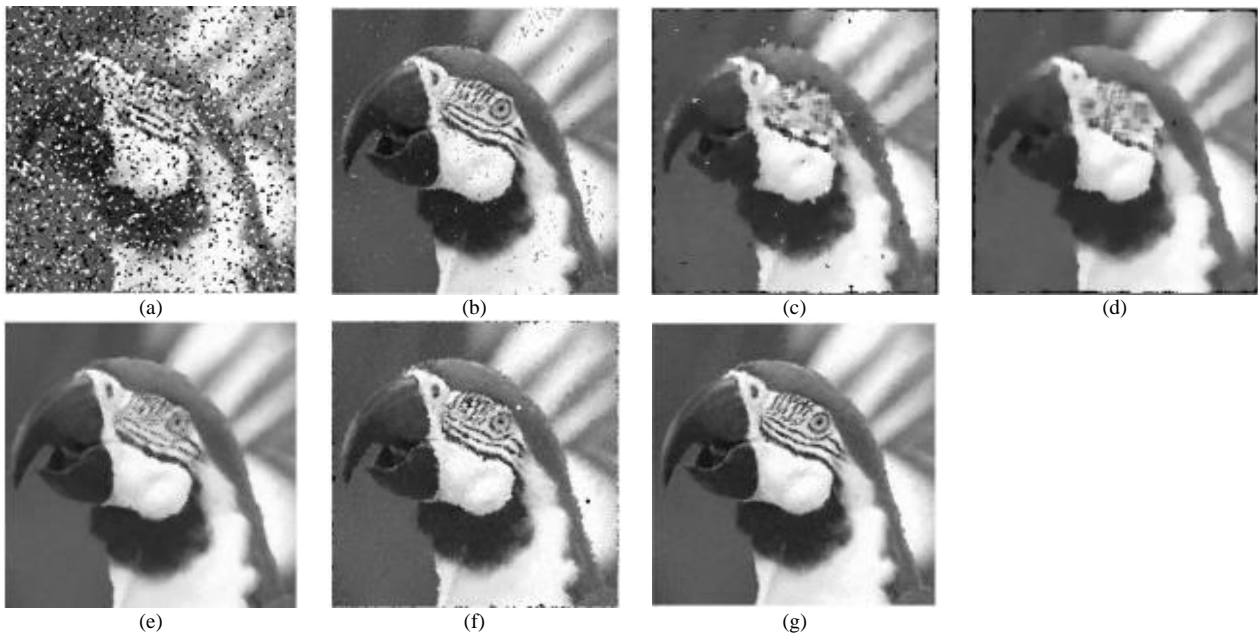


Fig.8. Results of denoising corrupted image “Parrot,” with 60% impulse noise density (a)DBA (b)MDBUTMF (c)AMF(d)NAFSM(e)BDND(f)CM and (g) FEIND

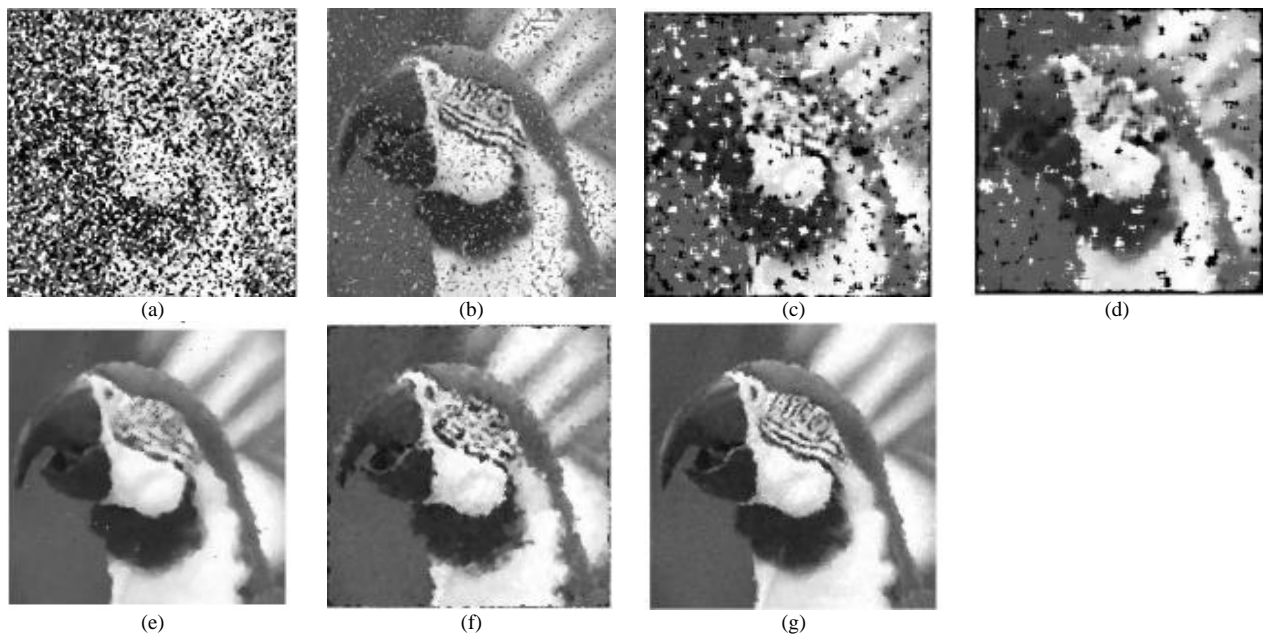


Fig.9. Results of denoising corrupted image “Parrot,” with 80% impulse noise density (a) DBA (b) MDBUTMF (c) AMF (d) NAFSM (e) BDND (f) CM and (g) FEIND

VI. CONCLUSIONS

In this paper, a novel filter with fuzzy entropy for impulse noise detection and removal has been proposed. It represents the uncertainties of the noise perfectly by using the fuzzy entropy, which is helpful in detecting and removing the noise. The experimental results show the FEIND filter is the good among the tested filters, compared with the traditional switching filters. No matter whether, in noise detection, the image details preservation or computational complexity, the FEIND filter makes a good improvement and has the higher performances. Even if the noise level closes to 90%, the texture, the details, and the edges of the images restored by the FEIND filter are preserved with good visual effect. FEIND is not giving the positive results for low impulse noise levels below the 30 % we will address this problem in next paper.

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