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Efficient Removal of Impulse Noise in Digital Images

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Abstract- Image Noise Suppression is a highly demanded approach in digital imaging systems. Impulsive noise is one such noise, which is frequently encountered problem in acquisition, transmission and processing of images. In the area of image restoration, many state-of-the art filters consist of two main processes, classification (detection) and reconstruction (filtering). Classification is used to separate uncorrupted pixels from corrupted pixels. Reconstruction involves replacing the corrupted pixels by certain approximation technique.

In this paper such schemes of impulsive noise detection and filtering thereof are proposed. Here we presents a comparative study on six methods such as median filter, Progressive switching median filter, Fuzzy switching median filter, Adaptive median filter, Simple adaptive median filter and its modified version i.e. Modified Simple Adaptive median filter. Objective evaluation parameters i.e. mean square error; peak signal-to-noise ratio is calculated to quantify the performance of these filters.

Index Terms- Median Filter, Progressive Switching Median Filter, Fuzzy Switching Median Filter, Adaptive Median Filter, Simple Adaptive Median filter

I. INTRODUCTION

Digital images which are related to digital signals are normally corrupted by many types of noise, including impulse noise [1]. Impulse noise is a set of random pixels which has a very high contrast compared to the surroundings. So, even a small percentage of impulse noise distorts the image greatly compared to other noises. Malfunctioning pixels in camera sensors, faulty memory locations in hardware, or transmission of the image in a noisy channel, are some of the common causes for impulse noise. The amplitude of the corruption is relatively very high compared to the strength of original signal. So, when the signal is quantized into L intensity levels, the corrupted pixels are generally digitized into either of the two extreme values (i.e. 0 or L-1). The impulse noise generally appears as white and black spots in the image.

Conventional median filtering approaches apply the median operation to each pixel unconditionally whether it is uncorrupted or corrupted. As a result, even the uncorrupted pixels are filtered and this causes degradation of image quality. To overcome this situation, some decision making process has to be incorporated in the filtering frame work. They are adaptive median filter and the median filter based on homogeneity information is called decision based or 'switching' filters. Here, the filter identifies possible noisy pixels and then replaces them with median value or its variants by leaving all the other pixels unchanged. On replacing the noisy pixels with some median value in their vicinity, the local features such as the possible presence of edges are not taken into account. Hence details and edges are not recovered satisfactorily especially when the noise level is high. When the noise level is over 50% some details and edges of the original image are smeared by the filter. This disadvantage can be overcome by using SAM and its modified version filter where a high degree of noise suppression and preservation of image sharpness can be achieved. SAM filter uses the intensity value of the pixels to determine the window size and also to identify whether the pixel is corrupted or uncorrupted. The window size is increased or decreased based on the amount of noises present in the input signal. After this selection, the output image produced by this filter with least mean square error is considered as input image for impulse noise detection which can be achieved by using SAM and its modified version filter.

II. MEDIAN FILTER (MF)

The Median Filtering [2] Technique can successfully remove Impulse noise from the distorted image but in this case the filtered image suffers the blurring effect. For the median filtering techniques each pixel is considered to calculate the median and also every pixel is replaced by that calculated median. So affected pixels are considered to calculate the median and unaffected pixels are also replaced by this calculated median. This undesirable feature prevents the median filtering techniques from providing higher PSNR or better quality image

III. PROGRESSIVE SWITCHING MEDIAN FILTER (PSMF)

The Progressive median filter (PMF) [4] is a two phase algorithm. In phase one noise pixels are identified using fixed size window (3x3). In second phase prior knowledge of noisy pixels are used and noise pixels are replaced by estimated median value.

Here, the difference of the median value of pixels in the filtering window and the current pixel value is compared with a threshold to decide about the presence of the impulse. Now a 3×3 window is taken whose central pixel is $x(i,j)$. In the Progressive switching median filter the output of the filter is given by:

$$y(i,j) = m_{i,j}\ ;\ \text{if } |m_{i,j} - x(i,j)| > \text{Threshold}$$
$$y(i,j) = x(i,j)\ ;\ \text{Otherwise} \qquad \text{------------------------------} \ (1)$$

where , $m_{i,j}$ represents the median value of the pixels inside the filtering window . Here median value is calculated same as in AMF without considering the corrupted pixel present in window. If calculated median value is less than minimum value present in window and greater than maximum value present in window then median value is treated as corrupted value. If calculated median is corrupted then increase the window size and recalculate the median value until we get correct median value or else window size reach maximum limit. When the above scheme is applied for impulse detection, a binary flag image $\{f(i, j)\}$is constructed such that $f(i,j)$=1, when the pixel $x(i, j)$ is noisy and $f(i,j)$=0 for noise less pixel. Now during filtering operation, the noisy pixels are replaced by the median of the noise-free pixels.This algorithm provide suitable and good results at smaller percent of noise level and find difficulty with higher level noises.

IV. FUZZY SWITCHING MEDIAN FILTER (FSMF)

This nonlinear filtering technique contains two separated steps: an impulse noise detection step and a reduction step that preserves edge sharpness. Noise detection method uses fuzzy gradient values to determine if a certain pixel is corrupted with impulse noise or not.

A.DETECTION USING FUZZY GRADIENT VALUES

For each pixel of the image (that is not a border pixel), we use a 3 x3 neighborhood window as illustrated in Fig. 1.Each neighbor with respect to corresponds to one direction {NW = North West, N = north, NE = north east, W = west, E = east, SW = south west, S = south, SE = south east}.Each such direction with respect to (i,j) can also be linked to a certain position indicated in Fig1. If we denote A as the input image, then the gradient then the gradient$\nabla(k,l)A(i,j)$ is defined as the difference

$\nabla(k,l)A(i,j) = A(i+k, j+l) - A(i,j)$ with $k,l \in \{-1,0,1\}$------------------------(2)

where the pair (k,l) corresponds to one of the eight directions and (i,j) is called the center of the gradient[3]. The eight gradient values (according to the eight different directions or neighbors) are called the basic gradient values.

One such gradient value with respect to(i,j) can be used to determine if a central pixel is corrupted with impulse noise or not, because if this gradient is quite large then it is a good indication that some noise is present in the central pixel , but there are two cases in which this conclusion is wrong.

1) If the central pixel is not noisy, but one of the neighbors then this can also cause large gradient values.
2) An edge in an image causes some kind of natural large gradient values.

To handle the first case, we use not only one gradient value, but eight different gradient values to make a conclusion.To solve the second case, we use not only one basic gradient for each direction, but also one basic and two related gradient values for each direction. The two related gradient values in the **same direction** are determined by the **centers** making a right angle with the direction of the first (basic) gradient. For example, in the *NW*-direction, we calculate the basic gradient value plus the two related gradient values. The two extra gradient values are used for making the separation between noisy pixels and edge pixels: when all these gradients are large, then is considered to be not a noisy but an edge pixel.

In Table I, we give an overview of the involved gradient values: each direction (column 1) corresponds to a position with respect to a central position. Column 2 gives the basic gradient for each direction; column 3 gives the two related gradients. Thus, we define eight fuzzy gradient values for each of the eight directions. These values indicate in which degree the central pixel can be seen as an impulse noise pixel.

TABLE 1
INVOLVED GRADIENT VALUES TO CALCULATE THE FUZZY GRADIENT

R	BASIC GRADIENT	RELATED GRADIENT
NW	$\nabla_{NW}A(i,j)$	$\nabla_{NW}A(i+1,j-1)$, $\nabla_{NW}A(i-1,j+1)$
N	$\nabla_{N}A(i,j)$	$\nabla_{N}A(i,j-1)$, $\nabla_{N}A(i,j+1)$
NE	$\nabla_{NE}A(i,j)$	$\nabla_{NE}A(i-1,j-1)$, $\nabla_{NE}A(i+1,j+1)$
E	$\nabla_{E}A(i,j)$	$\nabla_{E}A(i-1,j)$, $\nabla_{E}A(i+1, j)$
SE	$\nabla_{SE}A(i,j)$	$\nabla_{SE}A(i-1,j+1)$, $\nabla_{SE}A(i+1,j-1)$
S	$\nabla_{S}A(i,j)$	$\nabla_{S}A(i,j-1)$, $\nabla_{S}A(i,j+1)$
SW	$\nabla_{SW}A(i,j)$	$\nabla_{SW}A(i-1,j-1)$, $\nabla_{SW}A(i+1,j+1)$
W	$\nabla_{W}A(i,j)$	$\nabla_{W}A(i-1,j)$, $\nabla_{W}A(i+1,j)$

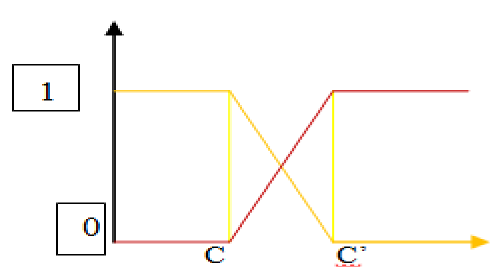
Since 'large','small','Big Positive', 'Big Negative' are non deterministic features ,these terms can be represented as fuzzy set [7] .Fuzzy sets are sets whose elements have degree of membership . Examples of the membership functions large, small, big positive and big negative are shown in Fig. 1a and 1b.

B.MEMBERSHIP FUNCTION

A membership degree indicates the degree in which a certain gradient value matches the predicate (e.g., large).

Since we are searching for noise pixels, we choose c $\in$[50,80] And c' $\in$ [100,150] .The idea behind the usage of the fuzzy sets *big positive* and *big negative* is that if the basic gradient and the two related gradients are both large but have different signs then it is a good indication that noise is present. Therefore, we also use the fuzzy sets *big-negative* and *big positive*. Gradient values around zero are seen as more or less unsigned and gradient values above 15 or under -15 become significant to matching the feature big positive, respectively, big negative.

Membership degree



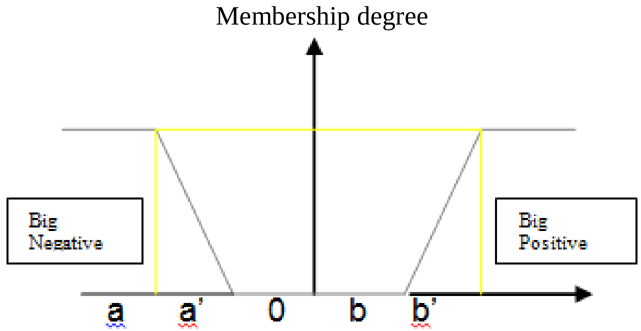


Fig.1. Membership functions (a) SMALL, respectively, LARGE; (b) BIG NEGATIVE, respectively, BIG POSITIVE

Correction method using switching median filter

To decide if a central pixel (a nonborder pixel) is an impulse noise pixel, we use following (fuzzy) rule:

IF | ▽R A(i, j)| is large AND | ▽'R A(i, j)| is small

OR

| ▽R A(i, j)| is large AND | ▽''R A(i, j)| is small

OR

▽R A(i, j) is big positive AND _ ▽'R A(i, j)
AND ▽''R A(i, j)_ are big negative

OR

▽R A(i, j) is big negative AND ▽'R A(i, j)
AND ▽''R A(i, j) are big positive
THEN ▽FR A(i, j) is large

We translate this rule by: if for a certain central pixel more than half of the fuzzy gradient values (thus more than four) are part of the support of the fuzzy set *large* , then we can conclude that this pixel is an impulse noise pixel.

Let xij and yij represent the pixel values at position (*i*,*j*) in the corrupted image and the restored image, respectively.The impulse detector generates a binary flag map where each pixel (*i*,*j*) is given a binary flag value, fij, indicating whether it is considered as an impulse; *i.e.*, fij =1 means the pixel in position (*i*,*j*) is a corrupted pixel and fij = 0 means the pixel in position (*i*,*j*) is noise free.To give the pixel *xij* a fuzzy flag indicating how much it looks like an impulse pixel, the following two parameter membership function is used for correction method.

$$fij = \begin{cases} 0 & Mij \le T1 \\ \frac{Mij-T1}{T2-T1} & T1 \le Mij \le T2 \\ 1 & Mij \ge T2 \end{cases} \quad \text{----------(3)}$$

Where Mij is the minimum value of I $xij - sij$ I , for all $sij \in wij$ and $sij \neq xij$ .T1 and T2 are two predetermine parameter given in [4],10≤T1≤20 and 22≤T2≤32 . If a pixel is detected as an impulse noise pixel, then we can calculate restore image value yij by using switching median value mij of window wij .i.e.

$$yij = (1 - fij) * xij + fij * mij \quad \text{-------------------------(4)}$$

And if pixel is noise free pixel (fij =0) then we copied it as it is means value is unchanged. i.e. $yij = xij$.For Heavily corrupted pixel,i.e. fij =1,its value is replaced by the median mij.for all other pixels (0< fij <1),the restored pixel value yij is a linear combination of xij and mij as in (4)

V. Adaptive Median Filter (AMF)

The adaptive median filter (AMF) [3] is non linear conditional filter. Here , the size of the median filter is made adaptable to the local noise content . Smaller filter size is applied at pixel locations with low noise level in order to keep the image details. On the other hand, larger filter size is applied at pixel locations with higher noise level in order to remove the noise successfully. Two levels of operations

- Level A:
  - A1= $Z_{med} - Z_{min}$
  - A2= $Z_{med} - Z_{max}$
  - If A1 > 0 AND A2 < 0, Go to level B
    else increase the window size by 2
  - If window size <= S_{max} repeat level A
    else output Z_{xy}
- Level B:
  - B1= $Z_{xy} - Z_{min}$
  - B2= $Z_{xy} - Z_{max}$
  - If B1 > 0 AND B2 < 0, output Z_{xy}
    else output Z_{med}

It uses varying window size to noise reduction. Size of window increases until correct value of median is calculated and noise pixel is replaced with its calculated median value. If calculated median is corrupted then increase the window size and recalculate the median value until we get correct median value or else window size reach maximum limit.

But in this type of filter there is limitation on size of window. So we are using another filter i.e. SAM, Simple Adaptive Median Filter which is the combination of adaptive median filter and switching median filter

VI. Simple Adaptive Median filter (SAMF)

It is the hybrid of adaptive median filter and Switching median filter Known as Simple Adaptive Median Filter [6].This novel method comprises two stages. The first stage is to detect the impulse noise in the image. In this stage, based on only the intensity values, the pixels are roughly divided into two classes, which are "noise-free pixel" and "noise pixel".

Noise Detection is done at each pixel location (x,y), we mark the mask α by using following equation

$$\alpha(x,y) = \begin{cases} 1; f(x,y) = L-1 \\ 0; otherwise \end{cases} \quad \text{----------(5)}$$

Where 1 represent 'noise –pixel' and 0 represent 'noise-free pixel'.Next , calculate the total number of 'Noise-Pixels'

$$k = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} \alpha(x,y) \quad \text{---------(6)}$$

Then , estimate the impulse noise level that corrupts the image

$$\eta = \frac{k}{MN} \quad \text{-----------------(7)}$$

Noise cancellation is done by using following equation

$$g(x,y) = [1-\alpha(x,y)] f(x,y) + \alpha(x,y) m(x,y) \quad \text{-------(8)}$$

Where α is the noise mask defined by (5) in stage 1 and m is the median value obtained from adaptive method.

Due to adaptive methodology ,the size of the filter used at every pixel location is changing according to the local information.

Median m(x,y) find by adaptive method

Initialize the size of the filter,generally with 3x3 wikndow, it is calculated by

$$W = 2R\min + 1 \quad \text{----------------------(9)}$$

Where

$$R\min = \frac{1}{2}\sqrt{\frac{7}{1-\eta}} \quad \text{-----------(10)}$$

Compute the number of 'noise-free pixel' in window. If number of noise -free pixels are less than half of pixels in the window, then increase the size of the filter by two i.e. W=W+2 and return to step 2. Calculate the value of m (x,y) based on the 'noise-free pixels' contained in WxW window.

Update the value of g(x,y) using (8) .

VII. Modified Simple Adaptive Median Filter (MSAMF)

Here we use a local window of size 21×21, which is centred around the current pixel. Calculate the histogram [3] of the local window and the bin indices are the gray levels. Find the maximum and minimum gray level of the local window, noted as Min and Max respectively. For the indices between Min and (*Min* +*Max*) / 2, compute differences of nonzero adjacent bin indices. Find the maximum difference and mark the corresponding index as boundary b1and b2 is similarly computed between (*Min* +*Max*) / 2 and Max, three clusters are formed now. "uncorrupted" is assigned to the pixel if it belongs to the median cluster; otherwise, "corrupted" is assigned. Now this detected pixel filtered using a binary matrix to indicate every pixel is corrupted or not, based on the binary decision matrix, those "uncorrupted" pixels are remain unchanged, while switching median filter with adaptive determined window size is applied to those "corrupted" pixel. Starting with window size W = 3, the filtering window extends one pixel in all the four sides of the window provided that the number of uncorrupted ones is less than 3. Suppose exploiting switch median filter to a noise pixel $x_{i,j}$ and finally decided window size is w_{max} and the output pixel $y_{i,j}$ is given as

$$y_{i,j} = median\{ x_{i+s,j+k} \mid -(w_{max}-1)/2 \le s,k \le (w_{max}-1)/2\} \qquad (11)$$

Attention that in the median filter process, those corrupted pixels are excluded; only those uncorrupted ones are considered to get median value. In filter process, if the number of uncorrupted pixels in filter window exceeds 3, extension stopped. So most of the finally decided window size w_{max} will not larger than 7, even for higher noise density level, so it is fast and suitable for higher noise density.

VIII. Simulation Results

The performance is compared and tested with different gray scale images (Lena and Pepper) and in the simulation, images will be corrupted by impulse noise with equal probability. The noise levels are varied from 10% to 90% with increments of 10%. These filters are applied to Lena and Pepper image , after adding impulse noise of different levels i.e. 10%-60%.The restoration performance is assessed according to the noise density of the corrupted pixels in the Lena and Pepper images. Both *PSNR*, *MSE* measure the difference in the intensity values of a pixel in original and enhanced images .It is measured in decibel (dB) and for gray scale image it is defined as

$$PSNR = 20\log_{10}\frac{255}{\sqrt{MSE}} \qquad (12)$$

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}[x(i,j) - y(i,j)] \qquad (13)$$

IQI measure is given by

$$Q = \frac{4\sigma_{xy}\overline{xy}}{(\sigma_x^2 + \sigma_y^2)(\bar{x}^2 + \bar{y}^2)} \qquad (14)$$

We assume that the image is of size M×N . IQI measures the similarity between two images. The definition of the new quality of index Let X = xi and Y = yi Where i = 1; 2; :::;N be the original and filtered images respectively. IQI is equal to 1 if both images are identical.

These values are calculated and comparison performance with various filters MF, PSMF, FSMF, AMF, SAMF, MSAMF are shown in Table-2 & Table-3.

TABLE-2

Table2:Comparison of PSNR of Cameraman and Lena at various noise conditions for various filters

Percentage of Noise	PSNR					
	MF	PSMF	FSMF	AMF	SAMF	MSAMF
Lena 20%	29.16276	32.02734	29.93355	34.38793	39.44658	41.43248
CM 20%	23.98603	25.13867	26.81751	27.99731	29.56197	31.67108
Lena 50%	15.01889	21.28433	18.552	20.9874	32.76267	34.93368
CM 50%	14.35945	18.71977	17.78448	19.74553	24.48182	26.07396
Lena 80%	7.739613	7.722932	9.350805	14.15797	24.45557	29.33685
CM 80%	7.699998	7.68929	9.31395	13.70817	19.12036	21.90337

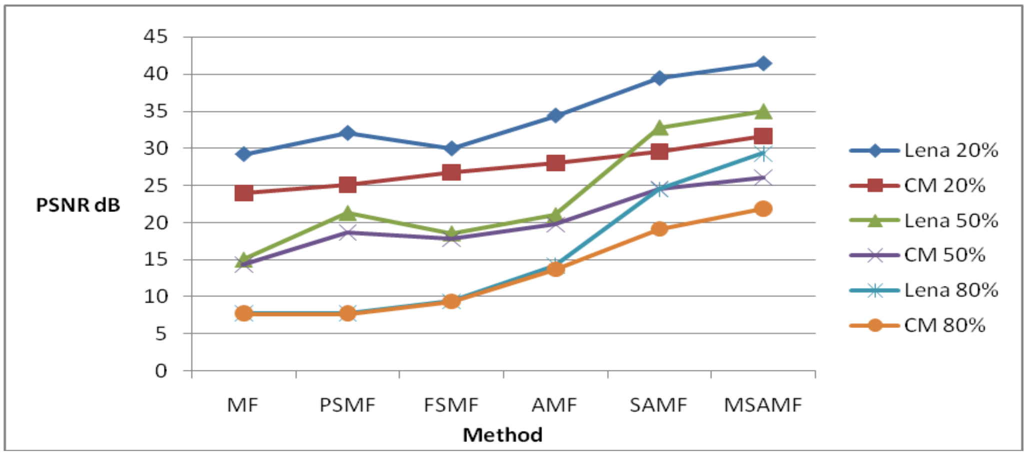


Figure 2: Graphical comparison of PSNR of Cameraman and Lena at various noise conditions for various filters

TABLE-3

Table3:Comparison of Image Quality Index (IQI) of Cameraman and Lena for various filters.

Percentage of Noise	IQI					
	MF	PSMF	FSMF	AMF	SAMF	MSAMF
Lena 20%	0.751269	0.870005	0.842474	0.856318	0.917788	0.960903
CM 20%	0.596327	0.795612	0.797354	0.768401	0.84667	0.930891
Lena 50%	0.176008	0.474843	0.292935	0.285153	0.828253	0.870911
CM 50%	0.171935	0.401826	0.291199	0.292039	0.718411	0.77972
Lena 80%	0.020268	0.021575	0.035696	0.084451	0.532156	0.684185
CM 80%	0.038812	0.040356	0.062209	0.110875	0.361299	0.514205

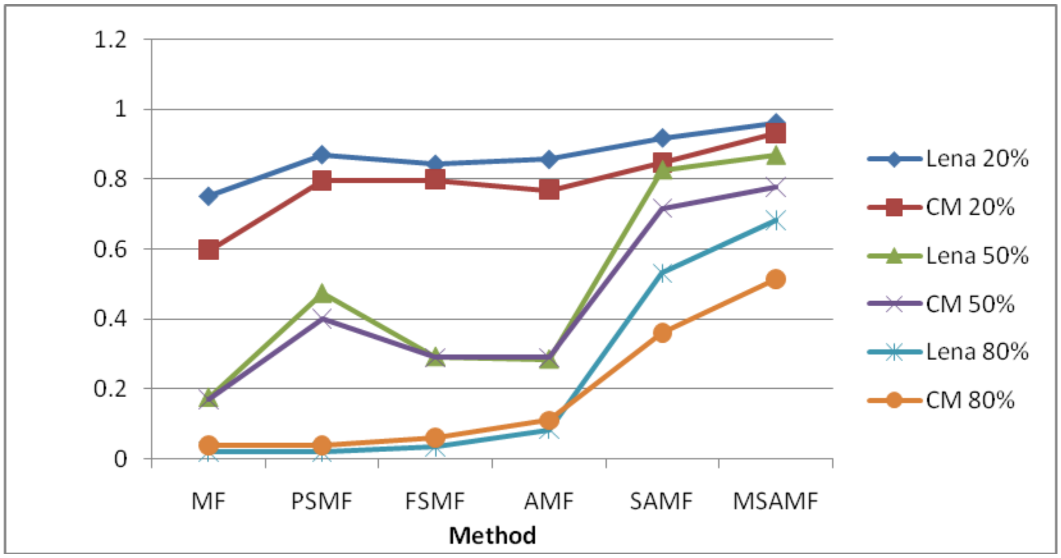
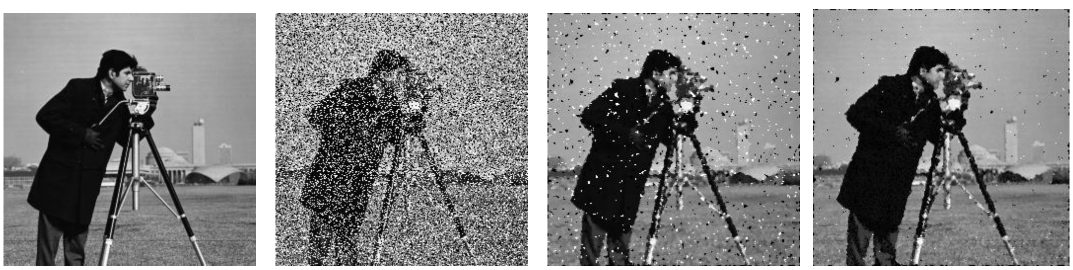


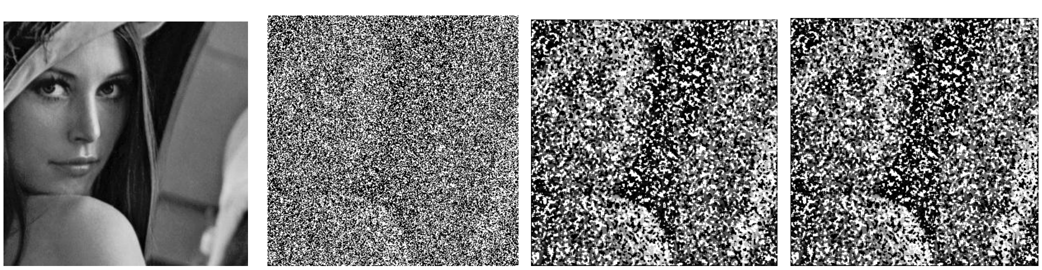
Figure3: Graphical comparison of Image Quality Index (IQI) of Cameraman and Lena for various filters.



Original 40% Corrupted by impulse noise MF PSNR 17.491dB PSMF PSNR 21.179 dB

FSMF PSNR20.713 dB AMF PSNR 22.322dB SAMF PSNR 26.471 dB MSAMF PSNR 27.726 dB

Fig.4 : Restored images of Cameraman(512x512) for MF, PSMF, AMF,FSMF,SAMF and MSAMF for 40 % Corruption by impulse noise.



Original 80% Corrupted by impuse noise MF PSNR 7.739 dB PSMF PSNR 7.723 dB

FSMF PSNR 9.351 dB AMF PSNR 14.159 dB SAMF PSNR 24.456 dB MSAMF PSNR 29.337 dB

Fig.5: Restored images of Lena (512x512) for MF, PSMF, AMF,FSMF,SAMF and MSAMF for 80 % Corruption by impulse noise

IX. CONCLUSION

In this paper a different non linear algorithms for impulse noise detection are compared and analyzed. SAMF and MSAMF algorithms efficiently handles high density noise i.e. noise ratio more than 50%. But for low density noise MF PSMF, FSMF, AMF perform better and give better PSNR value. FSMF takes slightly larger time as compare to other filter, but give very sharp image. So selections of filters depend upon noise density and images. Some filters are good for low noise and some for higher noise.

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