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Removal of Universal Impulse Noise by the Use of Second Order Neighborhood Mean Based Filter

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***ABSTRACT*–In digital image processing images plays a very vital role as humans can extract meaningful information from it. These images are very often degraded by images. There are various types of noises that affect the quality of digital images. These noises are Gaussian noise, Poisson noise, salt & pepper noise, Impulse noise, Speckle noise etc. But of these the two types of noise that affects the quality of digital images to a large extent are Impulse noise and Gaussian noise. This noiseespecially impulse noiseoccur in the images during image capture, transmission etc. For the detection and removal of impulse noise the mechanism is implemented. This mechanism consists of two stages: In the first stage, detection of noise is performed with the help of impulse detector. The second phase consists of filtering phase where noisy pixels are being repaired with the help of neighborhood mean based filter. This new approach works on both the impulse models – the random valued and /or fixed valued impulse noise models.**

Keywords -*Impulse noise, mixed noise, Impulse noise model, filtering techniques, fuzzy membership and PSNR.*

I. INTRODUCTION

Noise is defined as the any degradation in the image signal. This degradation is caused usually by the external disturbances. If theimage is sent from one place to another in the form of signals electronically, with the help of satellites or some networked cables, we may expect errors in the image signal [8]. These errors will also affect the quality of the image output in many different ways depending upon the type external disturbance that is introduced in the signal.

Now a days with the use of multimedia is increasing to a large extent, the visual information which we receive from high quality digital images plays a significant role in daily life applications. Noise is usually introduced in the images during image capture, transmission etc. The main causes of this type of noises are malfunctioning of image pixel elements, when faulty memory units are taken for each image pixel or when certain imperfections occurs in channels during transmission or when certain errors occurs during analog to digital conversion. Usually we know what type of errors is introduced in the image signal and the type of noise that an error produces on the image. Therefore we use certain standard mechanisms and techniques for the detection and removal of noise from image signals, while preserving the image fine details as well.

There are various types of noises that affect the information contains in the images to a large extent. Some of them are as follows; The Gaussian noise is characterized by adding a value with zero mean Gaussian distribution to each image pixel [1]. This type of noise really affects all the pixels in the image. Such noise is generally introduced in the image when the images are taken from external hardware devices like cameras etc.

Fig1. Images that represent Gaussian noise

Another form of noise is impulse noise also known as salt and pepper noise or spike noise or random noise or independent noise. This noise is usually characterized by replacing a portion of an image pixel with some noise values, without changing the other portions of the image. Such type of noise is introduced in the images when these images are taken from hardware devices like cameras or when the images are transmitted from one source to another in the form of signals. When these impulse noise affected images are viewed, they contain dark and white dots. These dots represent impulsive noise. Thus this noise is also referred as salt and pepper noise. This is so called salt and pepper noise because of the fact that it contains dark pixels in bright regions and bright pixels in dark regions.

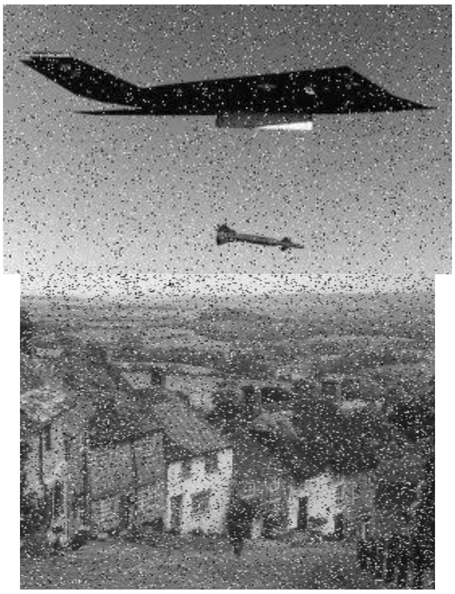

Fig2. Images that represent impulse noise

Another noise which usually affects the image transmission is speckle noise. This noise is characterized by multiplying random values to each image pixel values. Since this form of noise is multiplicative in nature, therefore it is also known as multiplicative noise. This noise has a major impact on many radar applications like measuring distances or map geophrical areas etc.

The quantization noise is another form of noise that is caused by quantizing the image pixels to a number of discrete levels. This form of noise has approximately uniform distribution on all the image pixels.

Based on the noise that is introduced in the images various detection and removal mechanisms have been proposed. For the removal of Gaussian noise and impulse noise various filters have been widely used. Recently various non-local methods like non local means (NL means), K-SVD, BM3D have been developed, and has shown great state of the art results [1]. Similarly for the removal of impulsive noise, development of different classes of filters such as median based filters, linear filters, adaptive filters, filters using soft computing and rank ordered statistics.These filters improve the performance of removal of impulse noise, but also increase complexity at the same time.

These filters have increased the performance for the removal of noise, but at the same time various fine image details have been lost. This is due to the fact that these filters have greatpotential for the removal of noise but they do not possess certain image restoration methods. Moreover these filters are not suitable for removal of impulse noise that is in between 25-90% noise density, because these filters donot possess sufficient restoration methods.Though there are certain mechanisms that also emphasis on image restoration along with noise removal. But this increases complexity to a large extent as well. Moreover the information obtained from the noisy images after the removal of impulse noise is not of significant level. This is so because the edges of the images are not well corrected after the removal of impulse noise. These filters which are being implemented operate on certain noise models which are discussed in the next section.

II. IMPULSE NOISE MODELS

The impulse noise models are based on non-stationary statistical characteristics and only certain percentage of pixels are affected by impulse noise [1][9]. The impulse noise model with probability ρ is defined as:

x (i, j) = o (i, j): with probability 1- ρ ……… (1)

f (i, j): with probability ρ

Where x (i, j) represents the pixel at location (i, j) with intensity x, o (i, j) and f (i, j) denotes original and noisy image respectively.

The two impulsive noise models which are used to define impulse noise in images are: the fixed valued impulse noise known as SNP (salt and pepper) noise and the random value impulse noise known as UNIF (uniform) noise. Out of these two impulse models the simplest and most commonly used model is the SNP noise model. The SNP impulse noise model assumes to take minimal and maximal intensities of the image pixels. On the other side the UNIF noise model can take any value within the range of maximal and minimal intensities.

If L_{max} and L_{min} are assumed to be the maximal and minimal intensities respectively, then for the SNP noise model the noisy pixels lies between maximal and minimal intensities of the entire image, that is f^{np}€ (L_{max}, $_{Lmin}$). The noisy pixel for the UNIF noise model lies within the dynamic range of maximal and minimal intensities, that is fnp € [L_{max}, $_{Lmin}$] respectively, where fnp denotes intensity of the noisy pixel in the image.The filters that were, discussed earlier works on one of the two impulse noise models (either SNP or UNIF). In real world applications, it is not easy to detect impulse noise without any priori knowledge. Thus we assume that any image that is being affected by impulse noise is a mixture of SNP and UNIF noise (also known as mixed noise).

Real impulse noise is some mixture between the SNF and UNIF noise, based on this fact the new impulse noise model can be defined as follows:

x (i, j) = o (i, j): with probability 1- ρ …. (2)

f^{unif} (i, j): with probability ρ/2

f^{snp} (i, j): with probability ρ/2

This model (discussed in eq. 2) is considered to be more for testing the performance of impulse noise filter. This new model is considered to be vital for implementing new mechanisms of filters because of the fact that in real worlds the noises especially the impulse noise is in the form of mixed noise. The mixed impulsive noise here means that the noisy pixel can take either the maximal intensity or minimal intensity or any value between maximal and minimal intensity respectively. Thus certain new mechanisms have to be developed based on the new impulse noise model described in equation no.2. Though there are filters based on fuzzy system that operates on both noise models with the help of second order absolute differences. But theseapproaches involve massive cost and computational time is also very high. Moreover the PSNR value (peak signal to noise ratio) in these filters is not that of significant level. The PSNR value is defined as the ratio between themost possible power of the signal and power ofthe corrupting noise that affects the images. This term is measure in logarithmic decibel scale. The higher PSNR value means high noise is being removed from the noisy images.

III. RELATED WORK

There are several mechanisms which are being implemented for the detection and removal of impulsive noise. The related work done in this field is as follows-: since each image pixel is made of three basic colors from which all the other colors are formed. It is well known that noisy pixels have either have high intensity or low intensity as compared to its surrounding pixels. So mechanisms is implemented which accepts an input image and filters all three primary colors (namely red, green and blue) respectively [8]. Then the impulse noise is filtered from these primary colors by using filtering techniques. This mechanism have drawback that these technique can only be used on one particular noise model (SNP or UNIF). With the increase in impulse noise and loss of image data various more filtering mechanisms have been implemented. The concept of functional dependency was also used between noisy sample images and random parameters which are used to remove noise in rendering system [6]. Over the years various filters have been implemented like those that are based on mean based filter, median based filter, linear filters, nonlinear filters etc. All these filtering mechanisms have shown a great promise in removing noise of impulsive nature. But the main drawback of these filtering mechanisms is that these filters operates and works on one noise model either salt and pepper noise or uniform noise model.

Over the years the importance of image retrieval and image restoration has been increased, because of the increase in demand of extracting information from images. Therefore one filtering mechanisms based on Robust outlyiness ratio (ROR) is being implemented. This mechanism evaluates standard deviation of the impulsive noisy pixel from the pixel without noise. Based on this deviation various rules are designed by which theses noisy pixels gets filtered [1]. The main drawback of this approach is that it also operates one noise model (SNP or UNIF). Moreover the overhead computational efficiency is also very high then to operate on both noise models, cluster based adaptive fuzzy logic switching median filter [9] is developed. This filtering approach takes both the noise model into account and evaluates second order difference values. This value then determines the clusters which consists of pixels values. The threshold value is also defined, based on this value the clusters are designed. Then the clusters with most noisy pixels are then filtered with the help of fuzzy logic. This is so because the image pixels have values either 0 or 1, whereas the impulsive noise pixels have values in the range of 0or1.

These mechanisms that are discussed above proves fruitful for the removal of various forms of noises (especially impulse noise), but these mechanisms include overhead computational time to be high and moreover this mechanisms have not shown greater reliability and robustness.

IV. PROBLEM STATEMENT

After studying the above literature we face some problems for the removal of impulse noise from digital images. In the spatial domain, the above filtering describes the optical system contains noise (spreads) a point of light Let I is the original true image and n is the additive noise, introduced during image acquisition that corrupts the image. Our aim is to minimize the noise as a degradation function that, together with an additive noise term, operates on an input image f(x,y) to produce a denoisy image, where f(x,y) is a degraded image. Many existing filters that only focus on a particular impulse noise model. In our work we focus on the filter is capable of filtering all kinds of impulse noise with fuzzy approach e.g. the random-valued and/or fixed-valued impulse noise models.

V. PROPOSED WORK

Since in real world applications when images are being captured by external devices like camera etc, the impulse noise that is being introduced in an image is a mixed noise (as discussed earlier). All the filters that are based on median based, cloud computing based operates on particular noise model that is they either operates on SNP noise model or on UNIF noise model. Although fuzzy logic median based filter is implemented that operates on the mixed impulsive noise. But this filter increases the complexity and overhead computational time to a certain level. Moreover the PSNR value for noisy pixel is not of that significant level from which useful information can be extracted. To work on mixed impulse noise we have introduced the new filter which is based on the concept of neighborhood. Here the meaning of neighborhood means that the noisy pixels which are surrounded by the other normal pixels. Moreover in this paper we also focus on developing a filter that can manage any types of impulse noise models (discussed in section II). This filter is known as second order neighborhood mean based filter.

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Figure 3: The original 'Lena' test image and 'Peppers' test image

In this approach, we first determine the grid (that is m*n) where m determines rows and n determines columns respectively. With the help of grid also known as windows, we are able to determine the central pixel which is surrounded by other neighboring pixels. Let x (i,j) here denotes the central pixels, then the first order absolute difference is being calculated. The first order absolute difference is evaluated by subtracting the central pixel x (i, j) from its surrounding neighboring pixels. These first order values are then arranged in ascending order. The purpose of arranging first order values is to index the values with the actual pixel values of the image from which the window size is being determined. Since it is known that noise pixels have intensities that vary from those of its neighboring pixels, by which the noise pixels can be identified and then can be filtered by filtering mechanisms. It is observed that first order absolute difference has discontinuity in its variation series where smaller values represent small differences and larger values represent large differences between central pixels and its neighboring pixels. To locate this discontinuity we calculate second order difference as subtracting the pixels which are arranged in ascending order by its neighboring pixel in the ascending order. The second order absolute difference values then helps in determine the number of clusters in which the pixel values have been determined. Let n determines the no. of clusters and $D^2(m)$ determines the second order absolute difference, and $T_d^{(t)}$ determines the threshold in the t-th iteration. All the indexed values will be in their respective clusters as long as they satisfy the criteria $D^2(m) <= T_d^{(t)}$. When $D^2(m)>T_d^{(t)}$ then the index values comes in the new clusters. From these clusters, the largest clusters that contains the most elements determines the set of noise free pixels in the window, whose size is being determined early. Furthermore the lower and higher boundaries for the noise pixels are determined by adding and subtracting the standard deviation from the lowest and highest intensitiesof the values that are specified in the clusters. This helps in making the detection of impulse noise more effective. After the detection of the impulse noise is being completed, a two dimensional binary decision map is used to determine position of noise free pixels and noisy pixels.

For the SNP noise model we consider a histogram where the peak intensities at the ends represent the noise intensities for the SNP. By using the concept of local maximums, from both the ends we can move towards the center of histogram.

Since the intensity of the noisy pixel in SNP model is either maximum or minimum, therefore the intensities can be represented here as L_{salt} and L_{pepper} respectively. In addition to a binary decision map, an additional master binary decision map is also used that keeps tracks of binary decision map at each levels of iteration. This master binary decision map is then updated with the help of OR operation on the entire image.

The proposed algorithm used is as follows:

1. Read the input Image I for size M*N. Scan each pixel (i, j) from image I in row major order. Create a 2-D window of size k x k pixels around the pixel (i,j) .The processing pixel is denoted as Pij.where i=1,2,….,M and j=1,2,…,N.
2. Determine the number of noise free pixels G (i, j) by calculating the no. of ones (1's) in the master binary decision map $B^{(t)}$ (i, j).
3. After the no. of ones is being evaluated, expand the window size W (i, j) from each of its four sides.
4. Apply noise detection method. If Pij is a noise free pixel then its value is unaltered. But If Pij is a noisy pixel then apply the proposed algorithm to the processing pixel.

4(a): In the selected window (k x k) if all the elements are not 0's and 255's, then compute the fuzzy membership value and replace Pij with the restoration term.

4(b): If the selected window contains all the elements as 0's and 255's, Then Increase the window size by one and again check increased window. If increased window contains all 0's then again increase window size by one. This process is repeated until we have a window with some element (except 0) on it or maximum window size limit reached. Then eliminate 0 from the window and find the median of the remaining pixels, and replace p_{ij} with mean value.

5. Then with the help of noise free pixels the mean pixel is being computed for the current window size. The men pixel M (i,j) is computed as follows :
   M (i, j): mean {x (i+p, j+q)} for all p, q.
6. Then we can extract local information D (i,j) from W (i,j) through:
   D^1 (i, j) = max {D^1 (m)}= D_s ((2Ld+1)^2-1). This means extracting local information from first order absolute difference or second order absolute difference.

7. Then we will compute the fuzzy membership value F(i,j) that is based on the local information obtained from the above step:
   F (i, j) = 0….............................D_1 (i, j) < T_1
   1. 0…………………...D_1 (i, j) < T_2
   D_1 (i, j) –$T_{1/T2-T1}$…..........T_1<= D_1 (i, j) < T_2

   Here T_1 and T_2 are the two predefined thresholds. In this way the noisy pixel is being detected and filtered

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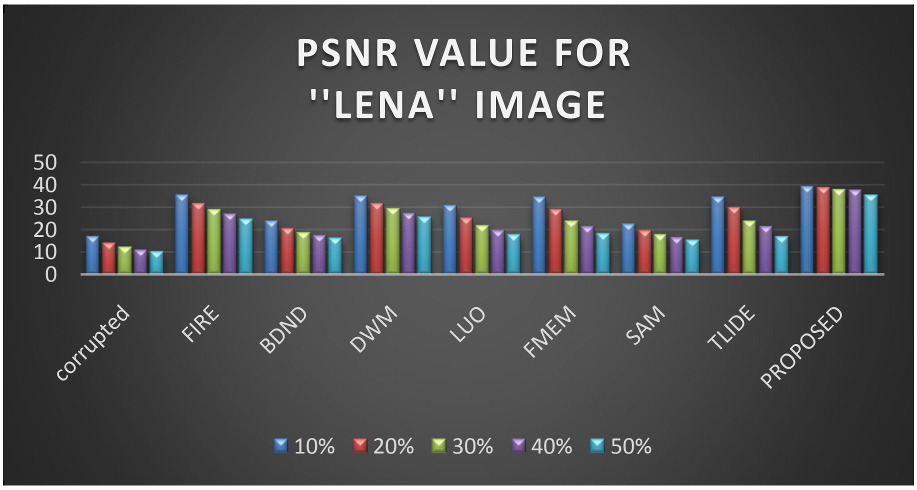
The following computations and calculations have been performed on the Lena test image which is given below and the table is being generated that compares the value of PSNR value (dB) of my proposed algorithm with the earlier versions of the filter. The comparison of our proposed algorithm for the two images that is "LENA" and "PEPPER" image (given above in fig. 3) along with the various previous filters is done. Based on these comparisons the graphs are also created.

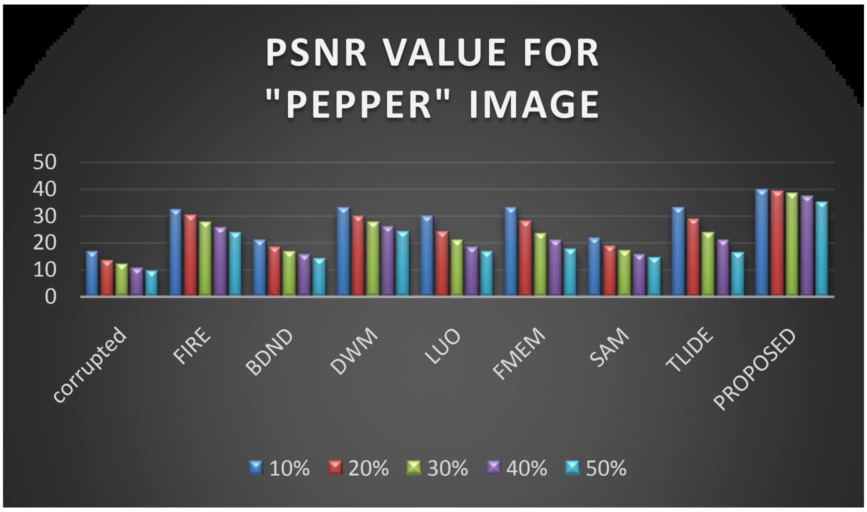
Table 1. Comparison of the restoration results for the "LENA" test image in PSNR (dB)

METHODS			PSNR (db)		
	10%	20%	30%	40%	50%
corrupted	16.93	13.91	12.15	10.92	9.96
FIRE [11]	35.16	31.49	28.96	26.63	24.49
BDND [12]	23.64	20.41	18.55	17.06	15.78
DWM [13]	34.82	31.3	29.24	27.05	25.33
LUO [14]	30.71	24.98	21.73	19.37	17.46
FMEM [15]	34.19	28.68	23.73	20.96	17.99
SAM [6]	22.25	19.24	17.47	16.26	15.29
TLIDE [8]	34.42	29.5	23.87	20.99	16.63
PROPOSED	**39.15**	**38.5**	**37.93**	**37.41**	**35.07**

Table 2. Comparison of the restoration results for the "PEPPERS" test image in PSNR (dB)

METHODS			PSNR (db)		
	10%	20%	30%	40%	50%
corrupted	16.93	13.91	12.15	10.92	9.96
FIRE [11]	35.16	31.49	28.96	26.63	24.49
BDND [12]	23.64	20.41	18.55	17.06	15.78
DWM [13]	34.82	31.3	29.24	27.05	25.33
LUO [14]	30.71	24.98	21.73	19.37	17.46
FMEM [15]	34.19	28.68	23.73	20.96	17.99
SAM [6]	22.25	19.24	17.47	16.26	15.29
TLIDE [8]	34.42	29.5	23.87	20.99	16.63
PROPOSED	**39.15**	**38.5**	**37.93**	**37.41**	**35.07**





VI CONCLUSION

In this paper we propose a new detection and filtering mechanisms that are based on the impulsive noise of mixed nature. This mechanism is more efficient than the various other filtering mechanisms, because of the fact that our proposed mechanisms is based on both the noise that is SNP as well as UNIF noise, whereas the past mechanisms only focus on either of the one impulse noise. Moreover with the use of my proposed algorithm the value of PSNR that is measured in dB is greater than the other filters which are used before. The greater the PSNR value means, the greater noise is removed from the images. Moreover to calculate noisy pixels we use the mathematical term mean, because this is more useful for comparing large sets of data as compared to various others measures of central tendency.

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