Salt and Pepper Noise Removal using Conditional Norm-Mean Filter

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Abstract -In this paper, a Conditional Norm filter is proposed to reconstruct noise affected images. A two step method has been incorporated, comprising of Noisy pixel recognition followed by restoration. Initially the noisy pixels are selected and a corresponding binary flag image is generated. Then the conditional norm operation is applied on each of the noisy pixel and replacement is done by the calculated value. The values hence obtained are further smoothed by reapplying the Neighbourhood Norm-Mean operation. This proposed algorithm shows better results than the Standard Median Filter (SMF), Decision Based Algorithm (DBA), Decision based un-symmetric Trimmed Median filter (DBUTMF) and Modified Decision based un-symmetric Trimmed Median filter (MDBUTMF). This filter clearly outperforms the existing filters with respect to MSE and PSNR comparison. It also shows to be robust to very high levels of noise, retrieving meaningful detail at noise levels as high as about 90%.

Keywords: Neighbourhood Norm-Mean operation, SMF, DBA,MSE, PSNR, Salt & Pepper, Filter, Restoration

I. INTRODUCTION

Grains which are visible in images are the variations in the intensities of an image and are known as Noise. Each image consists of pixels having varied intensity. To reduce this feature (noise) in images different noise removal filters can be utilized. The function of these filters is to make the image more clear and smooth. But sometimes it appears as unclear or unidentified result in various cases. Among various noises in images, Impulse Noise, also called as spike noise or independent noise, is a good example. This noise when featured in an image gives a colour combination of black and white dots, and hence they are also known as salt and pepper noise. Noises in image are formed due to changes of image signals. Other factors like dust or problematic articles can also create this type of noise. Here the noisy pixels can be taken in either maximum or minimum gray levels (255 or 0 respectively).This produces some white and black dots having maximum and minimum value respectively.

In this paper a conditional norm filter is proposed where norm is calculated in different stages and noisy pixels are approximated by checking with a prefixed threshold value. The proposed filter outperforms the above discussed filters in high noise densities (70%-90%). The paper has been divided into sections where section II illustrates the prototype of the process used, section III shows the literature survey, section IV illustrates the proposed methodology, section V represents the experimental results, section VI portrays the conclusion and section VII provides a way for the future scope of this project.

II. SYSTEM MODEL

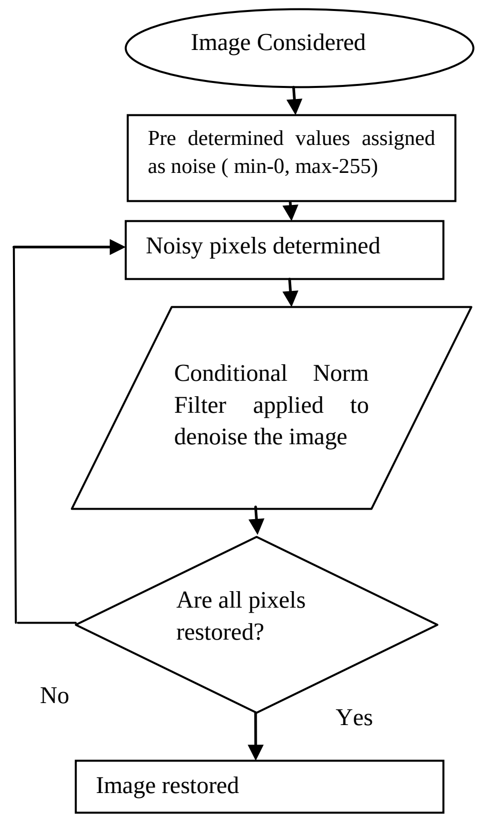


Fig.: Model of the proposed filter used on Images

III. PREVIOUS WORK

Some effective noise filters were that used by A.Kundu(1984) for replacing every pixel by the mean of all the pixels in 3×3 mask centred around the pixel. The drawbacks of this pixel considering even the non-noisy pixel lead to the introduction of the Standard Median Filter by Tukey, which replaced every pixel by the median of the 3×3 mask centered around the pixel. Further the Decision Based Algorithm (DBA) came through; which had the advantage of selecting only the corrupted pixel and replacing it by the replacement method. Then the Decision based un-symmetric Trimmed Median filter (DBUTMF) and Modified Decision based un-symmetric Trimmed Median filter (MDBUTMF) was introduced which had the advantage that the actual value could be regained from the mean if all the pixels were noisy in the 3x3 window, though this filter didn't perform good in the noise density 70%-90%. Effective noise removal at high noise density is still un-achievable using the above mentioned filters.

IV. PROPOSED METHODOLOGY

Here we consider $x_{i,j}$ for (i,j) Є A ≡ {1,2,3,…M} × {1,2,3,……N} be the gray intensity level at pixel location (i,j) of a true M×N image G. A salt and pepper noisy grayscale image G_1 (M×N) is taken where a pixel having intensity value '0' or '255' will be considered as a noisy one. The proposed method consist of two segments: (a) noise detection and (b) restoration

(a)Noise detection : The image G_1 (M×N) is taken and every pixel is considered for checking. Concurrently a same size binary flag image F_1 (M×N) is generated where $f_{i,j}$is considered a pixel value at the location (i,j).

if$x_{i,j}$=0 or $x_{i,j}$=255
then
$f_{i,j}$=0
else
$f_{i,j}$= $x_{i,j}$

Repeating the above procedure a same size image G_2 (M×N) is generated.

(b)Restoration: The noisy image has to be restored after being affected by salt & pepper noise. We perform the Restoration using the Conditional Norm Operation.

STEP–1: Replacement by Conditional Norm Operation

Consider G_2 (M×N) for (i,j) starting from (2,2) to (M-1,N-1).
If $x_{i,j}$=0 and ($x_{i-1,j}$, $x_{i+1,j}$, $x_{i,j-1}$, $x_{i,j+1}$) $\neq 0$ then
Replace $x_{i,j} = \sqrt{(\sum_{k=i-1}^{i+1} \sum_{r=j-1}^{j+1} (x_{k,r})^2)}/n$
Where n is the number of non-noisy pixels in the image.
Repeating the above procedure image G_3 (M×N) is generated.

STEP–2: Neighborhood Norm-Mean Operation

The image G_3 (M×N) is taken. Consider G_3 (M×N) for (i,j) starting from (2,2) to (M-1,N-1).
Taking $x_{i,j}$ as the center we create a (3×3) matrix. Calculate for each pixel in the said matrix
A1=($\sqrt{((x_{i,j-1})^2+(x_{i,j})^2+(x_{i,j+1})^2)}$)/3
if ($x_{i,j}$) > A1
then A2=($x_{i,j}$) – A1
else
A2=A1 - ($x_{i,j}$)

After completing this process an image G_4 (M×N) is generated.

STEP–3: Threshold Comparison & Flag Image re-creation

If A2 is greater than the pre-fixed threshold value=18, then,
$f_{i,j}$ =1
else
$f_{i,j}$ =0
Repeating the above procedure a Flag image F_2 (M×N) is generated.

STEP–4: Flag Image converted to the noisy image

In F2 If ($f_{i,j}$ =1) Replace $f_{i,j}$ =0.
Examine G_4 (M×N) for (i,j) starting from (2,2) to (M-1,N-1). pixels Repeat STEP-1until all the pixels are traversed.

The above procedure is performed so that the transformed pixels that exceed the threshold value are once again denoted as noisy and hence the Selective Mean is re-applied to ensure ultimate noise removal.

STEP–5: Border Operation

i. Upper Border Mean Calculation

Examine F_2 (M×N) for (i,j) starting from (1,2) to (1,N-1) .
if $x_{i,j}$ =0 then
replace $x_{i,j}$ =($\sqrt{((x_{i,j-1})^2+(x_{i,j+1})^2)}$)/2
If adjacent pixels corresponding to $x_{i,j}$ are '0' then consider the next neighborhood pixels(both in the left and right direction) for row wise replacement.

ii. Left Border Mean Calculation

Examine F_2 (M×N) for (i,j) starting from (2,1) to (M-1,1) .
if $x_{i,j}$ =0 then
replace $x_{i,j}$ =($\sqrt{((x_{i-1,j})^2+(x_{i+1,j})^2)}$)/2
If adjacent pixels corresponding to $x_{i,j}$ are '0' then consider the next neighborhood pixels(both above and below the column) for column wise replacement.

iii. Right Border Mean Calculation

Examine F_2 (M×N) for (i,j) starting from (2,N) to (M-1,N) .
if $x_{i,j}$ =0 then

replace $x_{i,j} =(\sqrt{(x_{i-1,j})^2+(x_{i+1,j})^2})/2$

If adjacent pixels corresponding to $x_{i,j}$ are '0' then consider the next neighborhood pixels (both above and below the column) for column wise replacement.

iv. Lower Border Mean Calculation

Examine F_2 (M×N) for (i,j) starting from (M,2) to (M,N-1) .
if $x_{i,j}$ =0 then

replace $x_{i,j} =(\sqrt{((x_{i,j-1})^2+(x_{i,j+1})^2})/2$

If adjacent pixels corresponding to $x_{i,j}$ are '0' then consider the next neighborhood pixels(both in the left and right direction) for row wise replacement.

The four corner pixels, i.e. (1,1), (M,1), (1,N), (M,N) are replaced by the mean of the adjacent neighbourhood uncorrupted pixels.

V. SIMULATION/EXPERIMENTAL RESULTS

The proposed method is appraised on the base of Mean Square Error (MSE), Peak Signal-to-Noise Ratio (PSNR).The outputs obtained of the proposed work are tested step-wise and the results are shown in Fig.3. Quantitative performances of the de-noising techniques are measured by Mean Square Error (MSE), Peak Signal-to-Noise Ratio (PSNR) as defined in equation (1) and (2) respectively.

$$MSE=\left(\sum_{M,N}\frac{\left(I(m,n)-\hat{I}(m,n)\right)^2}{M\times N}\right) \quad (1)$$

MSE is the mean square error between original image (I) and de-noised image ($\hat{I}$). M and N are the number of rows and columns in the input image, respectively.

$$PSNR = 10\log_{10}(255^2 / MSE) \quad (2)$$

Table 1.shows the psnr comparison with respect to Lena image for different existing filters with the proposed filter at variable noise density(50%-90%).

Fig.1. and Fig.2.shows the visual result of Proposed filter after application on Barbara and Cameraman image respectively. Fig.3. shows the quality of the reconstructed image for different filters compared to the proposed filter at 60% noise density. Table.2. illustrates the comparison of MSE between different filters with the proposed at varied noise density (50%-90%). Both qualitative and quantitative result shows that the proposed filter outperforms the above stated filters in all respect.

TABLE 1.
PSNR FOR DIFFERENT FILTERS FOR LENA IMAGE AT DIFFERENT NOISE DENSITIES

Image	**Filters**	50%	60%	70%	80%	90%
Lena	SMF	15.42	11.13	9.93	8.70	6.60
	DBA	26.42	24.81	22.62	20.37	17.11
	DBUTMF	27.08	25.52	23.41	20.93	17.92
	MDBUTMF	28.18	26.40	24.30	21.70	18.40
	Proposed	**30.10**	**29.52**	**27.86**	**26.61**	**25.02**

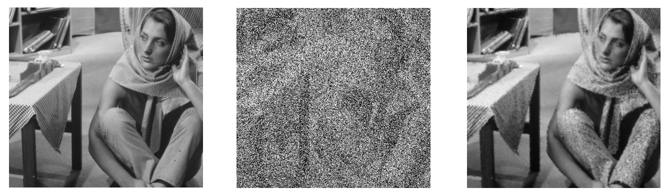


fig.1. Proposed filter on Barbara image: a) Original image b) 70% noisy image c) Output Image

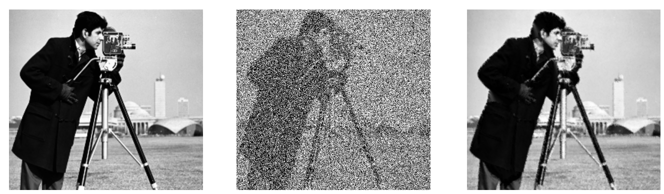
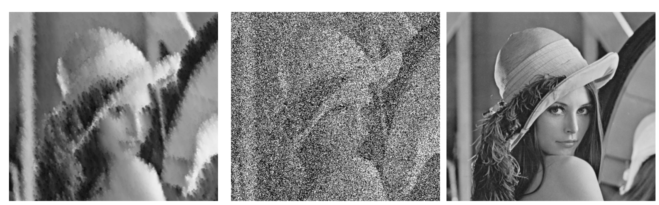
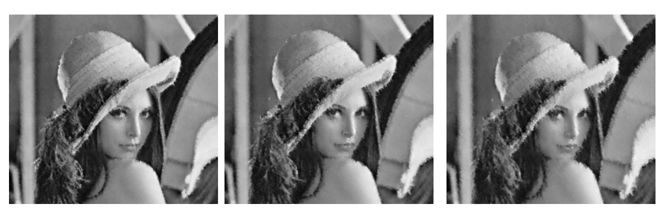


Fig.2. Proposed filter on Cameraman image: a) Original image b) 70% noisy image c) Output Image



(a) (b) (c)



(d) (e) (f)

(g)

Fig. 3. Comparison of output of different filters with the proposed filter: (a) Original Lena image (b) 60% noisy image (c) SMF (d) DBA (e) DBUTMF (f) MDBUTMF (g) Proposed

TABLE 2.
MSE FOR DIFFERENT FILTERS FOR LENA IMAGE AT DIFFERENT NOISE DENSITIES

Image	**Filters**	60%	70%	80%	90%
Lena	SMF	5047.54	6608.15	8771.63	14225.91
	DBA	215.31	357.33	597.14	1267.88
	DBUTMF	183.26	297.22	524.90	1054.88
	MDBUTMF	148.96	241.59	439.62	939.89
	Proposed	**72.95**	**107.91**	**142.25**	**210.41**

VI. CONCLUSION

In this paper, a noise reduction scheme for removing salt and pepper noise is proposed. The first phase of the scheme efficiently identifies impulse noise non-iteratively while the other removes the noise from the corrupted image to preserve the details and image quality. As per the experimental results, the proposed algorithm yields good filtering result for high density noise. This is observed by numerical measurements like PSNR and visual observations through the experiments conducted.

VII. FUTURE SCOPE

Further work on the proposed project is always possible, but with the growing amount of noise in images, we should aim to de-noise images on the basis of random values, that is, to determine a certain pixel as a noise by the value itself rather than predetermining pixels as noise or noiseless. Also, filters can be created to make the images perform good over 90% noise, to ascertain a more enhanced version of the image after restoration.

REFERENCES

[1] S. Banerjee, A Bandyopadhyay, R Bag, and A Das, “Neighborhood Based Pixel Approximation for High Level Salt and Pepper Noise Removal,” *CiiT International Journal of Digital Image Processing*, Vol. 6, No. 8, pp. 346-351, Nov, 2014.

[2] S. Banerjee, A Bandyopadhyay, R Bag, and A Das, “Moderate Density Salt & Pepper Noise Removal,” *IJECT* Vol. 6, Issue 1, Spl- 1 Jan – March, 2015.

[3] A. Bandyopadhyay, Shubhendu Banerjee, Atanu Das, and Rajib Bag,” A Relook and Renovation over State-of-Art Salt and Pepper Noise Removal Techniques,”*I.J. Image, Graphics and Signal Processing*, vol-9, pp-61-69, Aug, 2015.