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A Novel Iterative and Adaptive Noise Detection Method for Removal of Impulse Noise

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Abstract –

In this paper, the authors propose an efficient technique called Iterative and Adaptive Noise Detection Method (IANDM) for detecting the corrupted pixel in the image and for estimating the original value of the corrupted pixel. With the proposed method the noise pixel detection is improved by giving important to both the local and the global features. The proposed AMPMAD algorithm has a highest detection in terms of 99.99% for 15% corrupted pixels in Lena image. Further the authors propose an adaptive iterative mode replacement policy for estimating the values of corrupted pixels. The performance evaluation of the proposed noise detector is measured viz PFN and PFP. The quantitative evaluation of the filter measured in terms of PSNR and MSE.

Index terms – Impulse noise, Linear Noise Reduction filters, Non Linear Noise Reduction filters, Iterative and Adaptive filters

I INTRODUCTION

Images processing methods are implemented to handle various real time problems. Output of every method depending on the quality of input images. To get the quality of images various images enhancement or restoration techniques are use. Images enhancement techniques vary for different type's noise. Noise is any unwanted signal present in original signal. In Noise we have different noise types generated from different sources for example Impulse noise, Gaussian noise and speckle noise etc. Impulse noise is a major type of noise that causes image pixel values to be corrupted due to noisy environments like defective pixels in sensors. Based on the two noise variant of impulse noise are the salt-and-pepper noise and the random-valued noise. Whereas Gaussian noise increases or decreases the brightness of image and speckle noise produce big patches. Impulse and Gaussian noise are distributed uniformly but speckle noise is non uniform noise. Main cause of impulse noise is error in camera sensors or transmission cables [8].

II PREVIOUS TECHNIQUES AND DISCUSSION

Noise detection filters are basically classified into two types 1) Linear Noise Reduction Filters [LNRF] and 2) Non Linear Noise Reduction Filters [NLNRF]. In linear noise reduction techniques noise reduction formula is applied for all pixels of image linearly without differentiating pixel into noisy and non noisy pixels. In Non linear noise reduction is a two step process 1) noise detection and 2) noise replacement. In first step, location of noise is detected and in second step, detected noisy pixels are replaced by estimated value. Figur1 and figure2 represent the simulation results based on linear and non linear filters.

A. Average Noise Reduction Filters [ANRF]

A square window of size 2x+1 is used in average noise reduction filter [ANRF]. Here value of x changes from 1 to m. Window size (2x+1) is chosen only because window width and height must be odd so that we fix exactly central pixel (x+1, x+1). Using window original image is scanned row wise and column wise. Each time of scan value of central pixel of window is replaced by the average value of its neighboring pixels comes within the window.

B. Mean Noise Reduction Filters [MNRF]

Implementation of Mean noise reduction filters [MNRF] is similar to the Average noise reduction filters but here central pixel value is replaced by the mean value of its neighboring pixels comes within the window.

C. Median Noise Reduction Filters [M_eNRF]

Implementation of Median noise reduction filters [M_eNRF] is same to the Average noise detector but here central pixel value is replaced by the median value of its neighboring pixels comes within the window.

D. Min-Max Median Noise Reduction Filters [MMM_eNRF]

Min-Max Median Noise reduction filers [1] are primarily a non linear filter. In this non linear filter the (3x3) window is used for scanning the image left to right and top to bottom. The center pixel of window (2, 2) is chosen as a test pixel. If test pixel is less than minimum value present in rest of pixel in window and greater than maximum value present in rest of pixel in window. Then center pixel is treated as corrupted pixel and its value is replaced by median value of pixels present in window otherwise pixel is non corrupted pixel kept pixel value unchanged.

E. *Center Weighted Median Noise Reduction Filters [CWM$_e$NRF]*

An extension of the weighted median noise reduction filter is named as the Center weighted median noise reduction filter [CWM$_e$NRF] [2], which gives more weight to center values within the window. This noise reduction filter permits a degree of control of the smoothing behavior through the weights that can be set, and therefore, it is a promising image enhancement technique. These approaches involve a preliminary identification of corrupted pixels in an effort to prevent alteration of true pixel values. In this filter center pixel of (2x+1) square window considered as test pixel. If center pixel (x+1,x+1) less than minimum value present in rest of pixel in window and greater than maximum value present in rest of pixel in window then center pixel is treated as corrupted pixel. The corrupted pixel is replaced by estimated value of median. The Estimated value of median is calculated by rearranging all element of window in ascending order and taking median of elements from L_{th} element to $(N-L)_{th}$ element, where N is number of elements present in an array.

F. *Adaptive Median Noise Reduction Filter [AM$_e$NRF]*

The adaptive median filter [AM$_e$NRF] [3] is basically a non linear conditional filter. It implements varying window size to noise reduction. The size of window increases until correct value of median is calculated and noise pixel is replaced with its calculated median value. In this filter two conditions are used one to detect corrupted pixels and second one is to check correctness of median value. If test pixel is less than minimum value present in rest of pixel in window and greater than maximum value present in rest of pixel in window then center pixel is treated as corrupted pixel. 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.

G. *Progressive Switching Median Noise Reduction Filter [PSM$_e$NRF]*

The Progressive median noise reduction filter [PSM$_e$NRF] [4] is a two step method. In step one noise pixels are identified using fixed size window (3x3). If test pixel is less than minimum value present in rest of pixel in window and greater than maximum value present in rest of pixel in window then center pixel is treated as corrupted pixel. In second step prior knowledge of noisy pixels are used and noise pixels are replaced by estimated median value. Here median value is calculated same as in AM$_e$NRF 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.

H. *Tri-State Median Noise Reduction Filter [TSM$_e$NF]*

The Tri-State Median filter [TSM$_e$NF] [5] is a two step method. In step one noise pixels are identified using standard median filter. In second step prior knowledge of noisy pixels are used and noise pixels are replaced by Center weighted median noise reduction filter.

(a) Original Image (b) ANRF (c) MNRF (d) M$_e$NRF

Figure1. Outputs of (512x512) Television Lena Image.

(a) Original Image (b) Original Image With 50% Noise (c) MMM$_e$NRF (d) CWM$_e$NRF

(e) AM$_e$NRF (f) PSM$_e$NRF (g) TSM$_e$NF

Figure2. Outputs of (512x512) Television Lena Image

III PROPOSED METHOD

A. *Adaptive Maximum Pixel Based Noise Detector (AMPMAD)*

The basic idea of AMPMAD is to check each pixel with surrounding neighbors using variable window size (2n+1) × (2n+1) where n varies for 1 to 10. Evaluate each pixel with its neighborhood from coarse to fine using variable window size. The noise model considered is [7-8]

$$f(x)=\begin{cases} p, x(i,j)=0 \\ x(i,j), x(i,j)\in I \\ q, x(i,j)=255 \end{cases}$$

I – Pixel intensity and p, q – noise density levels, where $p \neq q$

The algorithm has two iterations. During the first iteration, a suitable detection map is generated by comparing with the histogram values. In the second iteration, the maximum absolute difference (MAD) map is generated based on the absolute difference value corresponding to the suitable window size. Choosing the minimum window size strictly depends on the noise density of the pixels in the image. A pixel x(*i*, *j*) is marked as "corrupted" if the MAD value is greater than the threshold value both in the current window and in all the chosen subsequent windows. Perhaps the most critical part of this paradigm is the determination of the threshold which is based on the local statistics. The incremental difference maximum value (MAD) of the respective window is compared with the window median, as the median value does not deviate much as window size increases for noiseless image. The window median of the suitable detection window is the local statistic used for decision boundary. The global minimum and maximum value are extracted from the histogram plot of the entire image gives the global statistic of the image and then MAD (Maximum of Absolute Deviation) statistic is estimated for the various windows sizes.

The noise detection for the various noise densities is as follows:

1. $x(i,j)\in(\max,\min)$, where (max, min) are from histogram plot (global statistics)

2. $\partial(k)=diff(k)^l=|x(i,j)-x(i+m,j+n)|$

Where $m=-(2n+1)$ to $+(2n+1)$ and $n=-(2n+1)$ to $+(2n+1)$ $k=1,2,3...(2n+1)^2$

The absolute difference vector $diff(k)^l$ is generated for variable length based on the window size length $l=1,2,\ldots 10$. The right values of l places the appropriate constraint on the current pixel for the suitable window size. The maximum pixel value map for the corresponding pixel detection map will be marked as "corrupted" if all the successive windows have the greater value than the local median calculated from the previous window size placed at the respective position.

3. Incremental MAD values = sort [$\partial(k)$] vector as $\partial_1, \partial_2, \partial_3, \ldots \partial m$

4. $\max(i,j)=\max\left(\partial(k)^l\right)$

The MAD Detection map has the following criteria met:

$$\max^{(2l+1)}<\max^{((2l+1)+2)}<..<\max^{((2l+1)+18-2(l-1))}$$

These criteria works based on the concept the maximum for a given window does not differ much in all the successive windows. (i.e.) $\partial_{\max_i}$ remains almost constant. The level *l* whose MAD value is greater than the pixel window median is chosen as detection window size. If both the conditions are satisfied, then MAD values are compared with pixel median is chosen to term whether the current pixel is corrupted or not.

B. *Adaptive Iterative Mode Replacement Policy*

In the lines of switching median concept, the pixel clusters that are termed as corrupted in the detection map are considered for the incremental median values. Generally, ∂_{med_i} remains values are within the threshold range of 10. This value is based on the experimental results applied on various images.

The next step is to find the window length for calculating the replacement of the corrupted pixel. This length will be same as the length that obtained for the $(max_i^{(2l+1)})_l$ MAD value subjected to the following criteria satisfied [8]:

$$pi\_med^{(2l+1)} < pi\_med^{(2l+1)+2} < pi\_med^{(2l+1)+4} \ldots\ldots\ldots\ldots < pi\_med^{(2l+1)+18-2(l-1)}$$

After finding the incremental median values termed as $\partial_{med_1}, \partial_{med_2}, \ldots.\partial_{med_{l-1}}$ the corrupted pixel is replaced with the suitable incremental median value obtained from the corresponding window size *l* fixed for the corresponding corrupted pixel. The same image is iteratively passed again through the detection and replacement process. The experiment using Lena image resulted in a significant improvement of PSNR by 10 dB, leaving the corner rows and columns proportional to the appropriate detection window size. An experimental research of this iteration for various images shows that, a maximum of six iterations is sufficient for maximum replacement beyond which no significant improvement in the MSE and PSNR is found.

IV PERFORMANCE MEASURES

A. *Performance evaluation of the proposed noise detector*

The noise detection capability of the proposed noise detector can be assessed mainly by two quality metrics namely number of false positives and the number of false negatives. False positive is the classification of original image pixel as noisy pixel whereas false negative is the classification of noisy pixel as noise free.

$$Percentage\ False\ Positive(PFP) = \frac{Number\ of\ false\ positives(FP)}{Total\ number\ of\ noise\ free\ pixels} \times 100$$

$$Percentage\ False\ Positive(PFN) = \frac{Number\ of\ false\ Negaives(FN)}{Total\ number\ of\ noisy\ pixels} \times 100$$

The table1 shows the PFP and PFN of the propose noise detector and the figure3 shows the plot for the PFP and PFN for various noise percentages.

B. Quantitative Evaluation of the Filter

The AMPMAD based image filter with various window sizes (3x3, 5x5,…, 13x13) are implemented for test images with noise intensity ranges from 5% to 90%. The visual quality of the filtered image can be assessed using the quantity viz. peak signal-to-noise ratio (PSNR) and mean square error (MSE).

Mean Square Error (MSE)

MSE between the original (X) and reconstructed $(\hat{X})$ image is defined as:

$$MSE = \left\| \frac{X - \hat{X}}{M\ N} \right\|$$

An MSE=0 in a reconstructed image indicates that $\hat{X}$ is a perfect reconstruction of X and (M, N) is the size of the image. Increasing values of MSE correspond to increasing error.

Peak Signal to Noise Ratio (PSNR)

PSNR in decibels (dB) between the original (X) and reconstructed $(\hat{X})$ image of size MxN is defined as:

$$PSNR = 20 \log_{10}\left(\frac{2^{B-1}}{\sqrt{MSE}}\right)$$

Where, B represents bits per pixel (bpp).

Figure4 shows the improvement in PSNR and MSE for the Lena image for 15% noise and table2 compares the filtering efficiency of variable window PWMAD and iterative variable window MAD.

Table 1: PFP and PFN for lena image (512 X 512) for the proposed noise detector for single iteration.

Noise (%)	PFP (%)	PFN (%)
10	0.32	1.98
20	0.88	3.1
30	1.73	4.8
40	3.38	8.1
50	5.61	12.56
60	7.65	16.64
70	10.18	21.7
80	13.78	28.9
90	18.56	38.46

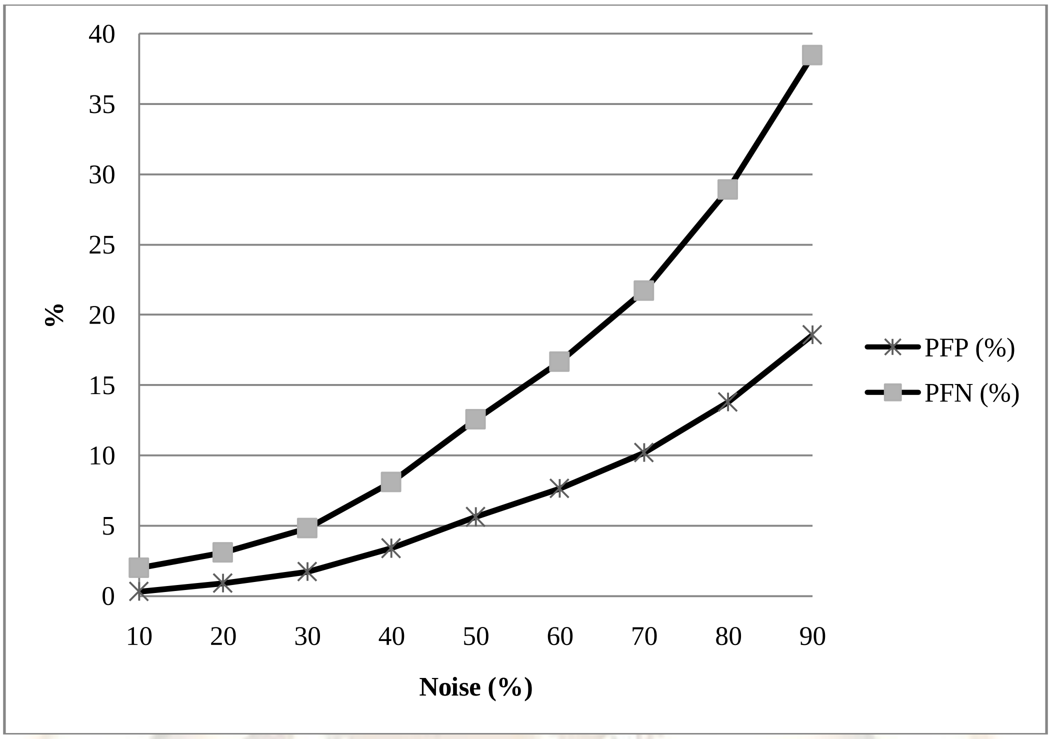
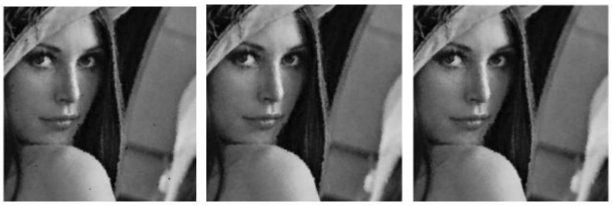


Figure3. Performance of noise detector for various percentage of noise level for single iteration

15% Noisy original | PSNR: 20.8504 dB MSE: 531.6143 | PSNR: 26.3087 dB MSE: 153.1297 | PSNR: 29.4873 dB MSE: 73.1732



PSNR: 31.3087 dB MSE: 49.1070 | PSNR: 31.8155 dB MSE: 42.8089 | PSNR: 31.8266 dB MSE: 42.6996

Table 2: Variable Window Mechanism and Iterative Window Method for various Noise Densities (lena image)

Noise density	Variable window PWMAD		Iterative variable window MAD	
	MSE	PSNR	MSE	PSNR
5 %	1.10	46.70	1.01	48.09
10%	2.73	41.77	2.36	43.40
15%	6.18	39.22	3.98	40.15
20%	12.12	35.67	4.92	37.73
25%	24.33	33.93	9.59	36.88
30%	46.07	30.50	11.39	36.86
35%	93.21	26.24	18.22	34.53
40%	168.44	25.82	21.83	32.54
45%	243.78	23.49	26.73	31.55
50%	377.47	21.31	35.25	32.54
55%	560.27	19.63	44.06	31.59
60%	778.85	18.21	53.72	28.75
65%	1105.60	16.69	85.54	27.71
70%	1429.70	16.57	106.42	26.78
75%	1879.50	15.39	225.37	22.60
80%	2449.60	13.24	411.13	19.97

V CONCLUSION

The proposed iterative and adaptive noise detection method dynamically computes the window length using the incremental maximum difference and incremental median value. The degree of variance between the windows centered at same pixel is exploited for detection and replacement policy. Extensive performance measures indicate that AMPMAD performs significantly better than many other existing techniques in impulse noise detection. The iterative procedure can effectively remove corrupted pixels with significant increase in PSNR value.

REFERENCES

[1] K. Satpathy, S. Panda, k k Nagwanshi and C Ardil, "Image Restoration in Non-Linear Filtering Domain using MDB approach", *International Journal of Signal processing*, 6:1 2010..

[2] subg-Jea KO and Yong Hoon, "Center Weighted Median Filters and Their applications to image enhancement", *IEEE Transactions on circuits and systems*, vol 38, no 9, September 1991.

[3] H Hwang and R A Haddad,"Adaptive Median Filter: New Algorithms and Results", *IEEE Transactions on image processing*, Vol 4 No 4 April 1995

[4] Zhou Wang and David Zhang, "Progressive Switching Median Filter for the Removal of Impulse noise from Highly Corrupted Images", *IEEE Transaction on circuits and systems-II : analog and digital signal processing*, Vol 46 No 1 January 1999.

[5] Tao Chen, Kai-Kuang Ma and Li-Hui Chen,'Tri-State Median Filter for Image Denoising", *IEEE Transactions on Image processing*, vol 8, no 12, December 1999.

[6] K.S. Srinivasan and D. Ebenezer, " A New Fast and Efficient Decision-Based Algorithm for Removal of High-Density Impulse Noises", *IEEE Signal Processing Letters* Vol 14 No 3 March 2007.

[7] A.K.Jain, "*Fundamentals of Digital Image Processing*", Engelwood Cliff, N. J.: Print ice Hall, 2006.

[8] P.G.Kuppusamy and R.Rani Hemamalini," An Iterative and Adaptive "Pixel Wise Maximum AbsoluteDifference (PMAD)" Based Image Filter for Impulse Noise Removal", *European Journal of Scientific Research*, Vol. 89 No 3 October, 2012, pp.422-429

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