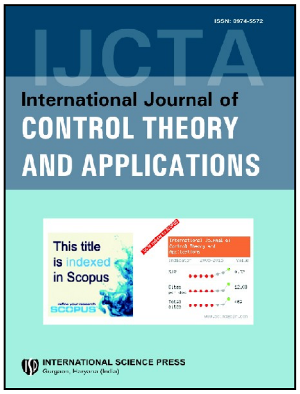

International Journal of Control Theory and Applications

ISSN : 0974-5572

Volume 10 • Number 29 • 2017

Improved Adaptive Median Filter Using 4-neighbors Based Restoration Technique for Restoration of Images Corrupted with Salt and Pepper Noises

Samsad Beagum[1*] and S. Sheeja[2]

[1]Research Scholar, Department of Computer Science, Karpagam University, Karpagam Academy of Higher Education Coimbatore, India
[2]Associate Professor and Head, Department of Computer Applications, Karpagam University Karpagam Academy of Higher Education, Coimbatore, India.
[1]Corresponding Author, E-mail: samsad.beagum@gmail.com*

Abstract: In this paper, we propose a restoration technique for adaptive median filter to improve its performance in efficiently eliminating salt and pepper impulse noise while preserving image details.

The improved adaptive median filter works in two stages. The first stage uses the adaptive median filtering technique to detect noisy pixels. In the second stage, the proposed restoration technique restores the noise candidates based on the corruption status of the 4-neighbors of the corrupted pixel that is obtained from the first stage. If atleast two of the neighbors of the noisy pixel are uncorrupted, the proposed technique replaces the noisy pixel with the median of the uncorrupted 4-neighbors. Otherwise it replaces the corrupted pixel with the median of the pixels in the filtering window. Images restored using our proposed algorithm and the quantitative performance measures have shown that the improved adaptive median filter algorithm outperforms the existing adaptive median filter algorithm in both preservation of image details and noise suppression. It is also shown that the performance measure of the improved AMF over the existing AMF improves with increasing noise density and it performs better for images with high activity.

Keywords: salt and pepper Noise, adaptive median filter, nearest-neighbor-based adaptive median filter, 4-neighbors based adaptive median filter.

1. INTRODUCTION

Impulse noise is caused by “transmission errors, malfunctioning of pixel elements in the camera sensors, faulty memory locations, or timing errors in analog-to-digital conversion” [1]. Impulse noise is classified as salt-and-pepper noise and random-valued impulse noise. Salt-and-pepper impulse noise takes the maximum and minimum gray level values in an image whereas the random-valued impulse noise takes any random gray level value in the dynamic range [0-255]. There are various filtering techniques in the literature for removing salt and pepper noise.

The median filter "is a simple nonlinear smoothing technique that takes the median value of the data inside a sliding window of finite length" [2] , [3]. Median Filtering is efficient in eliminating impulse noise and it preserves edges in images [4], but its performance deteriorates when the density of noise is high [12]. Several variations of median filters have been presented for detail preserving since the past three decades from max/ median [5], FIR-median hybrid [6], [7], multistage median [6], [8], adaptive median [9], to several variations of adaptive median fiters [10] - [16], [25] - [30].

The adaptive median filter is efficient in removing impulse noise and has less computational complexity than other image restoration techniques in literature such as the regularization methods or the partition-based methods [13], [18], [19]. However, it removes the image details just like median filtering [20] particularly when there is high noise ratio. In this paper, we propose a 4-neighbors based restoration technique for adaptive median filter. The improved algorithm has two stages. In the first stage, the algorithm uses the adaptive median filtering technique to detect pixels that are corrupted by noise. In the second stage, the algorithm computes the number of noise-free good pixels in the nearest four neighborhood. If there are atleast two noise-free 4-neighbors, the algorithm replaces the noisy pixel with the median of the uncorrupted 4-neighbors. Otherwise the algorithm replaces the noisy pixel with the median of the filtering window. It is shown that this restoration technique performs better than the existing adaptive median filter in preserving image details. It is also shown that the proposed filter shows significant improvement than the existing AMF algorithm in restoring images with high activity.

There are many "decision-based" median filters [22], [23], [24] that first detects the noise candidates using variant detection procedures and then replace the noise candidates by the median. As it is shown that our improved AMF restoration technique performs better than the existing AMF algorithm, it may be incorporated with any such "decision-based" noise removal technique for better performance.

The adaptive median filter is reviewed in Section II. The improved adaptive median filter is presented in Section III. Experimental results and conclusions are presented in Sections IV and V respectively.

2. ADAPTIVE MEDIAN FILTER - REVIEW

"The Adaptive Median Filter performs spatial processing to determine which pixels in an image have been affected by impulse noise. The Adaptive Median Filter classifies pixels as noise by comparing each pixel in the image to its surrounding neighbor pixels. The size of the neighborhood (detection window) as well as the threshold for the comparison is adjustable. A pixel that is different from a majority of its neighbors, as well as being not structurally aligned with those pixels to which it is similar, is labeled as impulse noise. These noise pixels are then replaced by the median pixel value of the pixels in the neighborhood that have passed the noise labeling test" [17].

Let X be the original image of size $M \times N$ and $X(i,j)$ denote the gray level of the pixel at location (i,j). Let the dynamic range of the pixel values in the image X be $[G_{min}, G_{max}]$ i.e. $G_{min} \le X(i,j) \le G_{max}$ for all (i,j). Let Y denote the image corrupted with salt-and-pepper impulse noise. Then the gray level value for any pixel $Y(i,j)$ is given by,

$$Y(i,j) = \begin{cases} G_{\min}, \ with\ probability\ r, \\ G_{\max}, \ with\ probability\ s, \\ X(i,j), with\ probability\ 1-r-s \end{cases}$$

where $n = r+s$ defines the noise level. Now, let G_w denote the filtering window of size $W´W$ centered at $Y(i,j)$ where $W = 2L+1$. The pixels in the filtering window are defined by

$$G_w = \{Y(u,v) : |u-i| \leq W \text{ and } |j-v| \leq W\}.$$

Let the maximum size of the filtering window used by the algorithme be $W_{max} \times W_{max}$. Here we present the algorithm for adaptive median filter. The algorithm works by testing if each pixel in Y is corrupted. If the pixel is found to be noisy, it is substitute with the median value of the pixels in the filtering window $G_{w.}$ Otherwise it leaves the pixel unaltered.

Algorithm for Adaptive Median Filter

For each pixel $Y(i,j)$ in the noisy image Y,

Step 1: Set $L = 1$, hence $W = 3$.

Step 2: Find the minimum, median and maximum pixel values of the detection window $\mathrm{G_w}$ as $\mathrm{G_{min,w}}$, $\mathrm{G_{med,w}}$, $\mathrm{G_{max,w}}$.

Step 3: If $\mathrm{G_{min,w}} < \mathrm{G_{med,w}} < \mathrm{G_{max,w}}$, then $\mathrm{G_{med,w}}$ is not an impulse, hence go to step 5. Otherwise set $\mathrm{L = L + 1}$, hence $W = W+2$.

Step 4: If $W \leq W_{max}$, go to step 2; else replace the pixel $Y(i,j)$ with $G_{med,Wmax}$.

Step 5: If $\mathrm{G_{min,w}} < Y(i,j) < \mathrm{G_{max,w}}$, then $Y(i,j)$ is not an impulse; else replace $Y(i,j)$ by $G_{med,w}$.

"The adaptive structure of the filter ensures that most of the impulse noise is detected even at a high noise level if the window size is large enough" [13]. However, this filter fails to removes the fine details from the image as the replacement is based on median filtering of the detection window.

3. PROPOSED IMPROVED ADAPTIVE MEDIAN FILTER

The improved adaptive median filter works in two stages. The first stage identifies the corrupted pixels using the adaptive median filtering technique and generates a binary flag image that specifies the corruption status of each pixel in the image. The second stage uses the 4-neighbors based restoration technique which checks the corruption status of the four neighbors of each pixel marked as corrupted in the binary flag image. If atleast two of the 4-neighbors of the noisy pixel are uncorrupted, the algorithm replaces the noisy pixel with the median of the uncorrupted 4-neighbors. Otherwise it substitutes the noisy pixel with the median value of the pixels in the filtering window.

Let C denote the binary flag image of size $M \times N$, that is used to hold the corruption status of every pixel in the noisy image Y. Initially $C(i,j) = 0$ for all (i,j).

Let Z be a matrix of size $M \times N$ used to hold the restored image. Initially let $Z(i,j) = Y(i,j)$ for all (i,j).

Stage 1:

For each pixel $Y(i,j)$ in the noisy image Y,

Step 1: Set $L = 1$, hence $W = 3$.

Step 2: Find the minimum, median and maximum pixel values of the detection window G_w as $G_{min,w}$, $G_{med,w}$, $G_{max,w}$.

Step 3: If $G_{min,w} < G_{med,w} < G_{max,w}$, then $G_{med,w}$ is not an impulse, hence go to step 5. Otherwise set $L = L + 1$, hence $W = W+2$.

Step 4: If $W \leq W_{max}$, go to step 2; else

i. Replace the pixel $Z(i,j)$ by $G_{med,Wmax}$.

ii. Set $C(i,j) = 1$.

Step 5: If $G_{min,w} < Y(i,j) < G_{max,w}$, then $Y(i,j)$ is not an impulse; else

i. Replace the pixel $Z(i,j)$ by $G_{med,w}$.

ii. Set $C(i,j) = 1$.

The stage 1 is the same as the existing algorithm except that for each corrupted pixel $Y(i,j)$, the median of the detection window is stored in $Z(i,j)$ and the binary flag image is set to 1. This difference is shown in italics in steps 4 and 5 of stage 1 above. After Stage 1,

$$Z(i,j) = \begin{cases} Y(i,j),\ if\ \ Y(i,j)\, is\, not\, an\, impulse. \\ G_{med,w}(i,j), if\ Y(i,j)\, is\, an\, impuse. \end{cases}$$

$$C(i,j) = \begin{cases} 0, if\ Y(i,j)\, is\, not\, an\, impulse. \\ 1, if\ Y(i,j)\, is\, an\, impuse. \end{cases}$$

Let $N = \{Y(i\text{-}1,j),\ Y(i+1,j),\ Y(i,j\text{-}1),\ Y(i,j+1)\}$ denote the four neighbors for the pixel at location (i,j) in Y and $F = \{C(i\text{-}1,j),\ C(i+1,j),\ C(i,j\text{-}1),\ C(i,j+1)\}$ denote the corruption status of those four neighbors respectively.

Stage 2:

For each pixel $Y(i,j)$ in the noisy image Y,

Step 1:

if $C(i,j) = 1$ i.e., if the pixel $Y(i,j)$ is noisy then,

if $F(i) = 0$ for atleast two values of i where $i = 0,1,2,3$ i.e. if atleast two neighbors of $Y(i,j)$ are uncorrupted then

i. Compute the median of the uncorrupted pixels among the four neighbors in F as N_{med}.

ii. Replace Z(i,j) with N_{med}.

Thus, for each pixel $Y(i,j)$ marked as corrupted by $C(i,j)$ the stage 2 just replaces $Z(i,j)$ with the median of the uncorrupted 4- neighbors.

4. EXPERIMENTAL SETUP AND RESULTS

Setup

We implemented the AMF algorithm and the improved AMF algorithm in MATLAB 7.6.0 in a Pentium Dual Core PC with 3GB RAM. We tested the algorithms with several standard 8-bit gray scale images of size 512x512, including the Lena image having homogeneous region and the Bridge image having high activity, with dynamic range [0,255]. For experimenting, the images are corrupted with salt and pepper noise in different densities using the MATLAB function imnoise. For computational efficiency the algorithms are implemented with the MATLAB's vector functions namely 'nlfilter' and 'find' that are used to compute the maximum, minimum and median of the sliding window for the entire image and to find the indices of noisy-free pixels in the neighborhood of each noisy pixel respectively.

The performance of our proposed method is also measured quantitatively by the peak signal-to-noise ratio (*PSNR*) and the mean absolute error (*MAE*) defined as [24]

$$PSNR = 10\log_{10}\frac{255^2}{\frac{1}{MN}\Sigma_{i,j}(Z_{i,j} - X_{i,j})^2}$$

$$MAE = 1/MN\,\Sigma_{i,j}\,|\,Z_{i,j} - X_{i,j}\,|$$

where $X_{i,j}$ and $Z_{i,j}$ and denote the value of the pixel at location (i,j) in the original and restored images respectively. The comparative performance measures for the two algorithms are shown in Table II and III.

RESULTS

The maximum window size chosen for different noise levels as per [13] is shown in table 1.

Table 1
Maximum Window Size Used

Noise level	W_{max} x W_{max}
< 25%	5x5
25% to 40%	7x7
41% to 60%	9x9
61% to 70%	13x13
71% to 80%	17x17
81% to 85%	25x25
86% to 90%	39x39

The results of applying the AMF and the improved AMF algorithms on the Lena and Bridge images corrupted with different noise densities are shown below. It is observed that the images restored by the improved AMF are sharper than those restored by the existing AMF algorithm.

It is also observed that the improved AMF restores the corrupted Bridge images significantly better than the existing AMF algorithm.

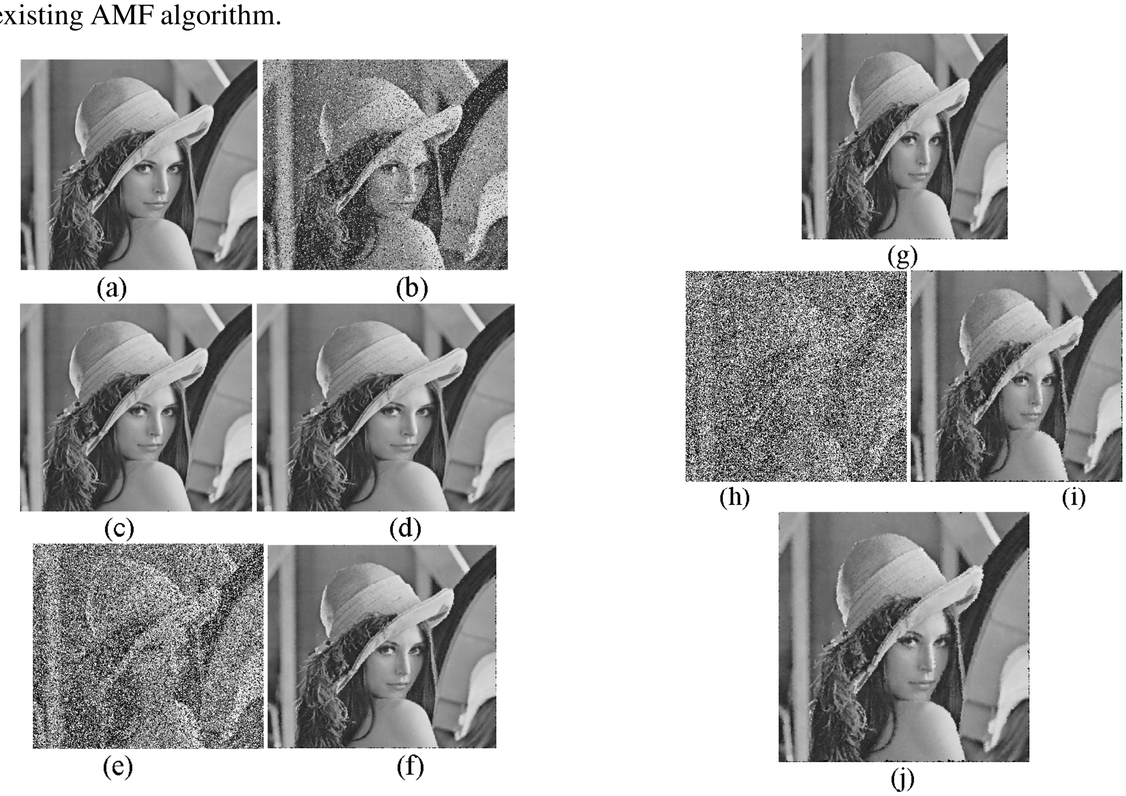

Figure 1: (a) Original image - Lena (b) Lena image corrupted with 15% salt and pepper noise. Image restored using (c) AMF using 5x5 window (d) Improved AMF using 5x5 window (e) Lena image corrupted with 50% salt and pepper noise. Image restored using (f) AMF using 7x7 window (g) Improved AMF using 7x7 window (h) Lena image corrupted with 70% salt and pepper noise. Image restored using (i) AMF using 13x13 window (j) Improved AMF using 13x13 window

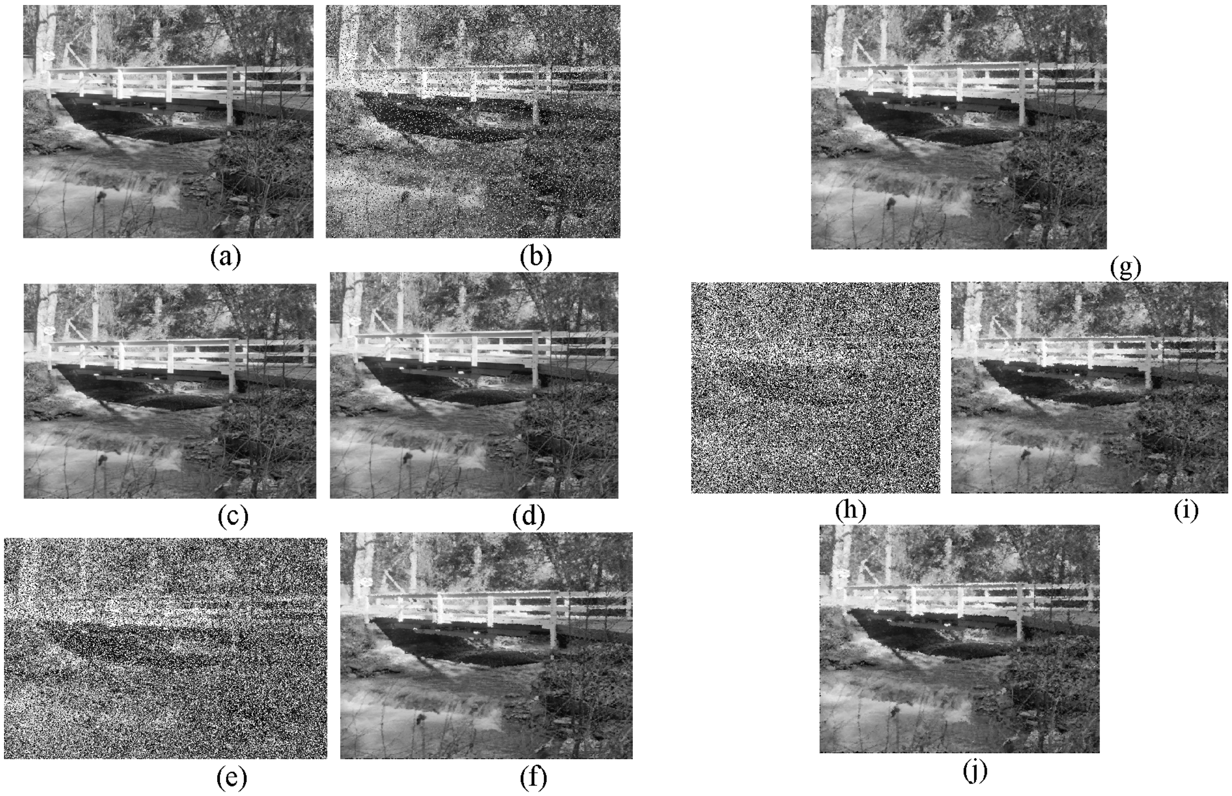

Figure 2: (a) Original image - Bridge (b) Bridge image corrupted with 15% salt and pepper noise. Image restored using (c) AMF using 5x5 window (d) Improved AMF using 5x5 window (e) Bridge image corrupted with 50% salt and pepper noise. Image restored using (f) AMF using 7x7 window (g) Improved AMF using 7x7 window (h) Bridge image corrupted with 70% salt and pepper noise. Image restored using (i) AMF using 13x13 window (j) Improved AMF using 13x13 window

Table 2
Comparative PSNR values of AMF and the proposed improved AMF on Lena and Bridge Images

Image	*Noise Density*	*AMF*	*Improved AMF*
Lena	10% (W_{max} = 5)	36.90	38.35
	15% (W_{max} = 5)	35.53	37.16
	20% (W_{max} = 5)	33.66	35.84
	30% (W_{max} = 7)	30.82	33.59
	40% (W_{max} = 7)	29.02	31.05
	50% (W_{max} = 9)	27.44	27.68
	60% (W_{max} = 9)	25.56	25.93
	70% (W_{max} = 13)	24.08	25
Bridge	10% (W_{max} = 5)	30.16	31.27
	15% (W_{max} = 5)	29.51	30.74
	20% (W_{max} = 5)	28.41	30.17
	30% (W_{max} = 7)	26.88	28.78
	40% (W_{max} = 7)	25.12	26.94
	50% (W_{max} = 9)	23.68	24.12
	60% (W_{max} = 9)	22.38	22.56
	70%(W_{max} = 13)	20.93	21.65

Table 3
Comparative MAE values of AMF and the proposed improved AMF on Lena and Bridge Images

Image	*Noise Density*	*AMF*	*Improved AMF*
Lena	10% (W_{max} = 5)	0.98	0.90
	15% (W_{max} = 5)	1.13	1.00
	20% (W_{max} = 5)	1.35	1.16
	30% (W_{max} = 7)	1.93	1.56
	40% (W_{max} = 7)	2.61	2.11
	50% (W_{max} = 9)	3.46	3.28
	60% (W_{max} = 9)	4.58	4.38
	70% (W_{max} = 13)	5.98	5.28
Bridge	10% (W_{max} = 5)	2.44	2.16
	15% (W_{max} = 5)	2.75	2.40
	20% (W_{max} = 5)	3.22	2.69
	30% (W_{max} = 7)	4.30	3.50
	40% (W_{max} = 7)	5.72	4.65
	50% (W_{max} = 9)	7.41	6.97
	60% (W_{max} = 9)	9.44	9.11
	70%(W_{max} = 13)	12.02	10.89

The tables 2 and 3 show that the improved AMF has given better measures than the existing AMF especially for the Bridge image. It is observed that the improved AMF shows significant progress in restoring images with high activity. The tables also show that the performance of the improved AMF filter increases with increasing noise density.

5. CONCLUSION

In this paper, we have presented a 4-neighbors based restoration technique for the adaptive median filter. The improved adaptive median filter outperforms the existing adaptive median filter especially in terms of preservation of fine details. The adaptive median filter has less computational complexity than many other restoration methods in literature like the regularization or the partition-based methods [13] [18] [19]. The experimental results show that the proposed restoration technique may be incorporated with any decision-based impulse noise restoration scheme for improving its performance.

REFERENCES

[1] I. Pitas and A.N. Venetsanopoulos, "Nonlinear Digital Filters: Kluwer Academic Publishers", 1990.

[2] L. Kitchen and A. Rosenfeld, "Gray-level corner detection", Pattern recognition letters, Vol. 1, No. 2, pp. 95-102, 1982.

[3] D.T. Kuan, A.A. Sawchuk, T.C. Strand and P. Chavel, "Adaptive noise smoothing filter for images with signal-dependent noise", IEEE transactions on pattern analysis and machine intelligence, Vol. 2, pp. 165-177, 1985.

[4] J. Astola and P. Kuosmanen, "Fundamentals of nonlinear digital filtering", Vol. 8, 1997.

[5] G.O.N.Z.A.L.O.R. Arce and M.I.C.H.A.E.L.P. McLoughlin, "Theoretical analysis of the max/median filter", IEEE Transactions on Acoustics, Speech, and Signal Processing, Vol. 35, No. 1, pp. 60-69, 1987.

[6] A. Nieminen, P. Heinonen and Y. Neuvo, "A new class of detail-preserving filters for image processing", IEEE Transactions on Pattern Analysis and Machine Intelligence, No. 1, pp. 74-90, 1987.

[7] P. Heinonen and Y. Neuvo, "FIR-median hybrid filters", IEEE Transactions on Acoustics, Speech, and Signal Processing, Vol. 35, No. 6, pp. 832-838, 1987.

[8] G.R. Arce and R.E. Foster, "Detail-preserving ranked-order based filters for image processing", IEEE Transactions on Acoustics, Speech, and Signal Processing, Vol. 37, No. 1, pp. 83-98, 1989.

[9] H.M. Lin and A.N. Willson, "Median filters with adaptive length", IEEE Transactions on Circuits and Systems, Vol. 35, No. 6, pp. 675-690, 1988.

[10] R. Ding and A. Venetsanopoulos, "Generalized homomorphic and adaptive order statistic filters for the removal of impulsive and signal-dependent noise", IEEE transactions on circuits and systems, Vol. 34, No. 8, pp. 948-955,1987.

[11] R. Bernstein, "Adaptive nonlinear filters for simultaneous removal of different kinds of noise in images", IEEE Transactions on Circuits and Systems, Vol. 34, No. 11, pp. 1275-1291, 1987.

[12] H. Hwang and R.A. Haddad, "Adaptive median filters: new algorithms and results", IEEE Transactions on image processing, Vol. 4, No. 4, pp. 499-502, 1995.

[13] R.H. Chan, C.W. Ho and M. Nikolova, "Salt-and-pepper noise removal by median-type noise detectors and detail-preserving regularization", IEEE Transactions on image processing, Vol. 14, No. 10, pp. 1479-1485, 2005.

[14] M. Juneja and P.S. Sandhu, "Design and development of an improved adaptive median filtering method for impulse noise detection", International Journal of Computer and Electrical Engineering, Vol. 1, No. 5, pp. 627, 2009.

[15] V.R. Vijaykumar and P. Jothibasu, "Decision based adaptive median filter to remove blotches, scratches, streaks, stripes and impulse noise in images", In 17th IEEE International Conference on Image Processing (ICIP), pp. 117-120, 2010.

[16] T.C. Lin and P.T. Yu, "Adaptive two-pass median filter based on support vector machines for image restoration", Neural Computation, Vol. 16, No. 2, pp. 333-354, 2004.

[17] *http://www.massey.ac.nz/~mjjohnso/notes/59731/presentations/AdaptiveMedian* Filtering.doc

[18] T. Chen and H.R. Wu, "Application of partition-based median type filters for suppressing noise in images", IEEE Transactions on Image Processing, Vol. 10, No. 6), 829-836.. 2001

[19] C. Wu, D. Chen and C. Zhao, "Impulsive noise filter using median-and partition-based operation", Optical Engineering, Vol. 47, No. 11, pp. 117004-117004, 2008.

[20] S.J. Ko and Y.H. Lee, "Center weighted median filters and their applications to image enhancement", IEEE transactions on circuits and systems, Vol. 38, No. 9, pp. 984-993, 1991.

[21] T. Chen and H.R. Wu, "Space variant median filters for the restoration of impulse noise corrupted images", IEEE Transactions on Circuits and Systems II: Analog and Digital Signal Processing, Vol. 48, No. 8, pp. 784-789, 2001.

[22] H.L. Eng and K.K. Ma, "Noise adaptive soft-switching median filter", IEEE Transactions on image processing, Vol. 10, No. 2, pp. 242-251, 2001.

[23] S. Zhang and M.A. Karim, "A new impulse detector for switching median filters", IEEE Signal processing letters, Vol. 9, No. 11, pp. 360-363, 2002.

[24] A. Bovik, Handbook of Image and Video Processing, Academic Press, 2000.

[25] T. Veerakumar, S. Esakkirajan and I. Vennila, "Edge preserving adaptive anisotropic diffusion filter approach for the suppression of impulse noise in images", AEU-International Journal of Electronics and Communications, Vol. 68, No. 5, pp. 442-452, 2014.

[26] Y. Song, Y. Han, J.S. Oh and S. Lee, "Edge Preserving Impulse Noise Reduction", Journal of Imaging Science and Technology, Vol. 57, No. 6, pp. 60507-1, 2013.

[27] H.C. Trivedi, U. Nilkanthan and A. Kumar, "Development of Salt-and-Pepper denoising techniques", In IEEE International Conference on Electrical, Computer and Communication Technologies (ICECCT), pp. 1-5, 2015.

[28] A. Dash and S.K. Sathua, "High Density Noise Removal By Using Cascading Algorithms", In Fifth International Conference on Advanced Computing & Communication Technologies (ACCT), pp. 96-101, 2015.

[29] Y. Wei, S. Yan, L. Yang and Y. Fu, "An improved median filter for removing extensive salt and pepper noise", In International Conference on Mechatronics and Control (ICMC), pp. 897-901, 2014.

[30] R.R. Kumar, K. Vasanth and V. Rajesh, "Performance of the decision based algorithm for the removal of unequal probability salt and pepper noise in images", In International Conference on Circuit, Power and Computing Technologies (ICCPCT), pp. 1360-1365, 2014.